EINDHOVEN UNIVERSITY OF TECHNOLOGY

Exploring a novel telescoping visibility graph methodology in physiological time series analysis

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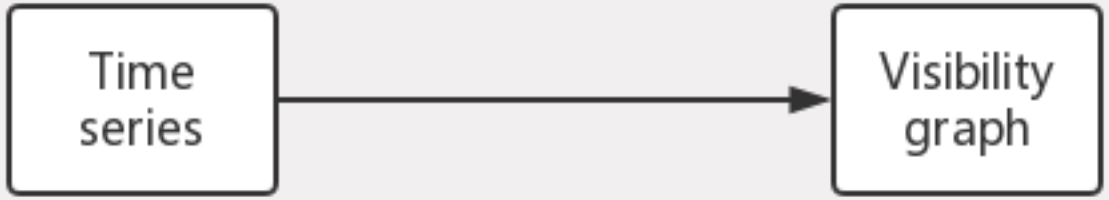
Content

Introduction – Background Information

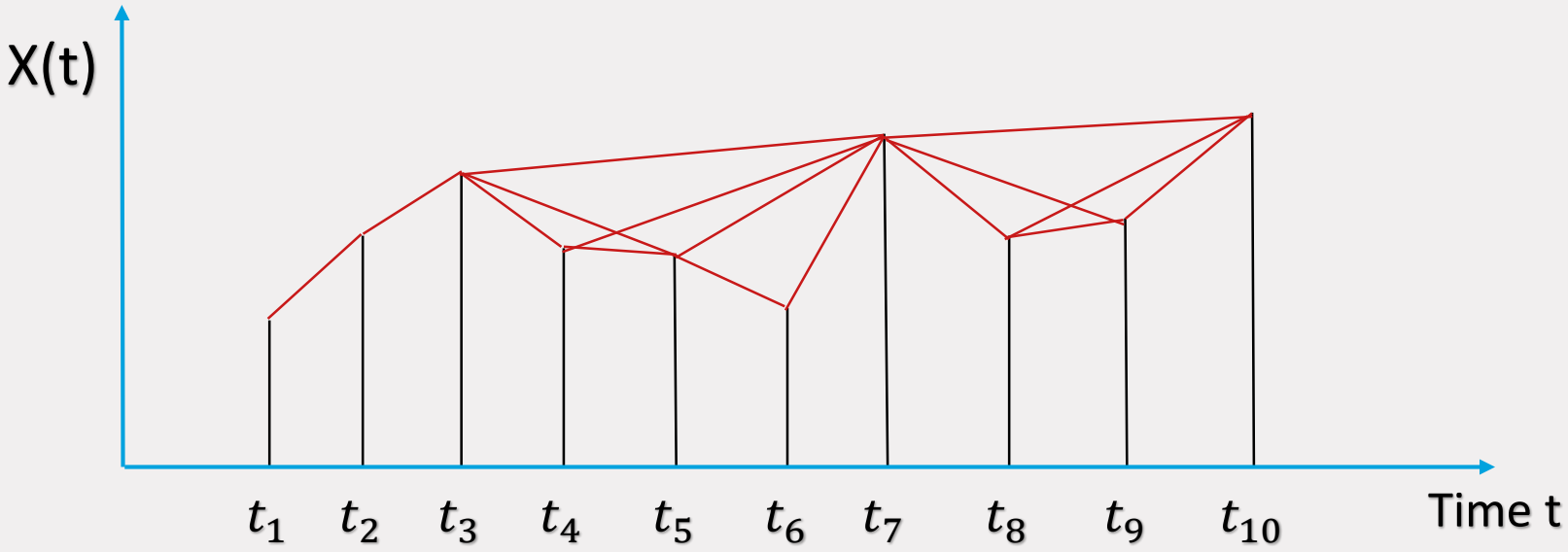
The visibility graph (VG) algorithm converts a time series into a complex network.
This process allows to apply methods of complex network theory for characterizing time series.

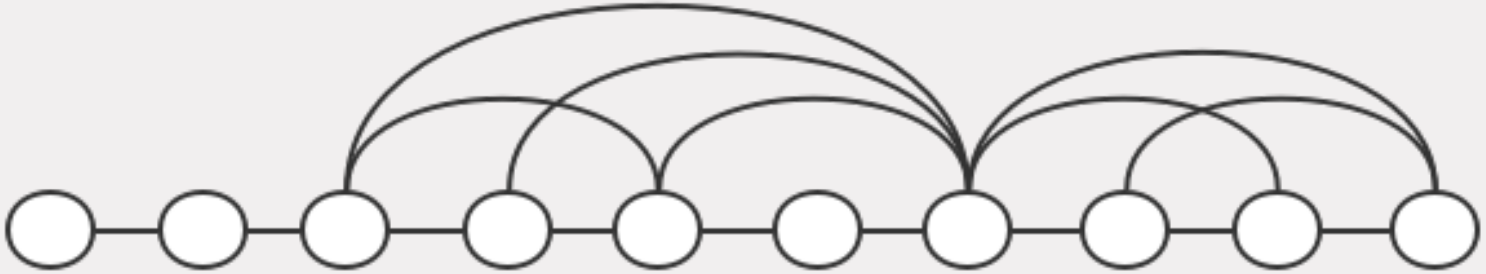


The existing VG algorithm:

- Basic VG (BVG)
- Horizontal VG (HVG)
- Difference VG (DVG)

Introduction – BVG method





Two arbitrary data values:
$(t_a, x(t_a)), (t_b, x(t_b))$
If any other data points
$(t_c, x(t_c))$
Between them satisfies:

$$\frac{x(t_c)-x(t_b)}{t_c-t_b} > \frac{x(t_b)-x(t_a)}{t_b-t_a}$$

$$a, b, c \in \{1,2 \dots 10\}$$

Introduction – Objective

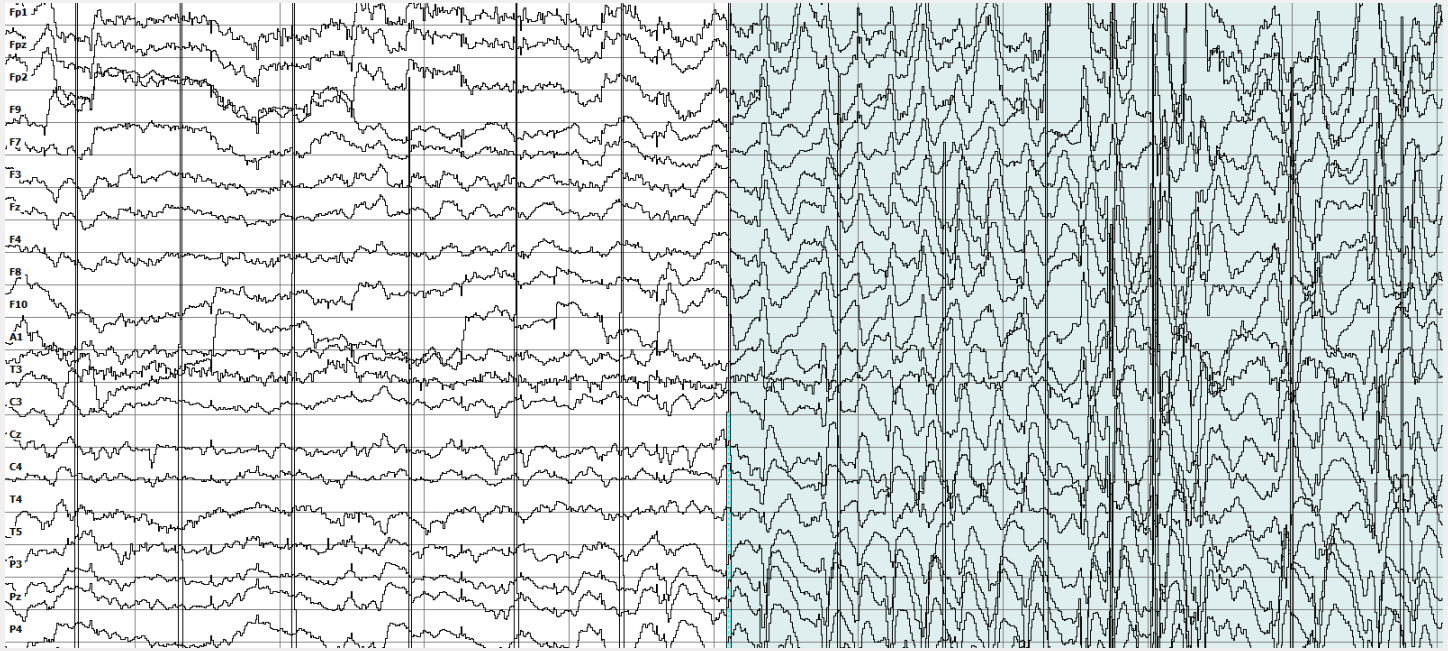
Telescoping VG (TVG)

The expectation of TVG is that it helps distinguish different kinds of time series through artificially changing the time series.

We expect that different kind of time series might response differently in complex network topology to artificially changing the time series, the features extracted from TVG may better distinguish different kind of time series than the existing VG method.

Introduction – TVG for nonconvulsive seizure detection

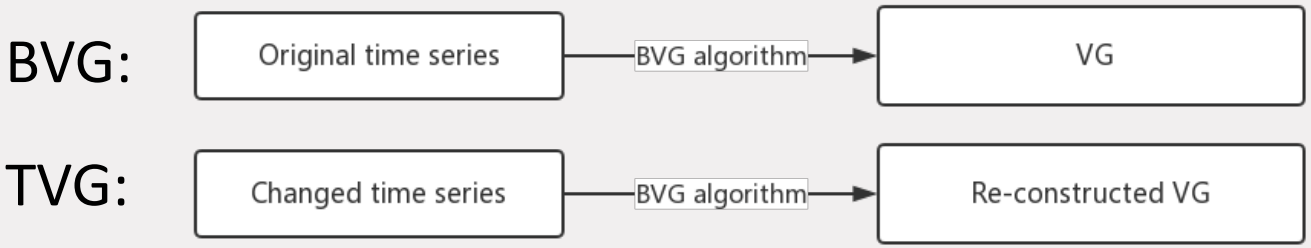
To verify the validity of TVG for real application with regard to signal classification, we also applied our proposed TVG methods on (electroencephalography) EEG signals in detecting nonconvolusive seizure, i.e. classifying ictal and non-ictal episodes.



Methods

- TVG trials

- Part One: TVG analysis on pseudo signals
  - Pseudo signals
  - Characteristics of VGs
  - Statistical Analysis



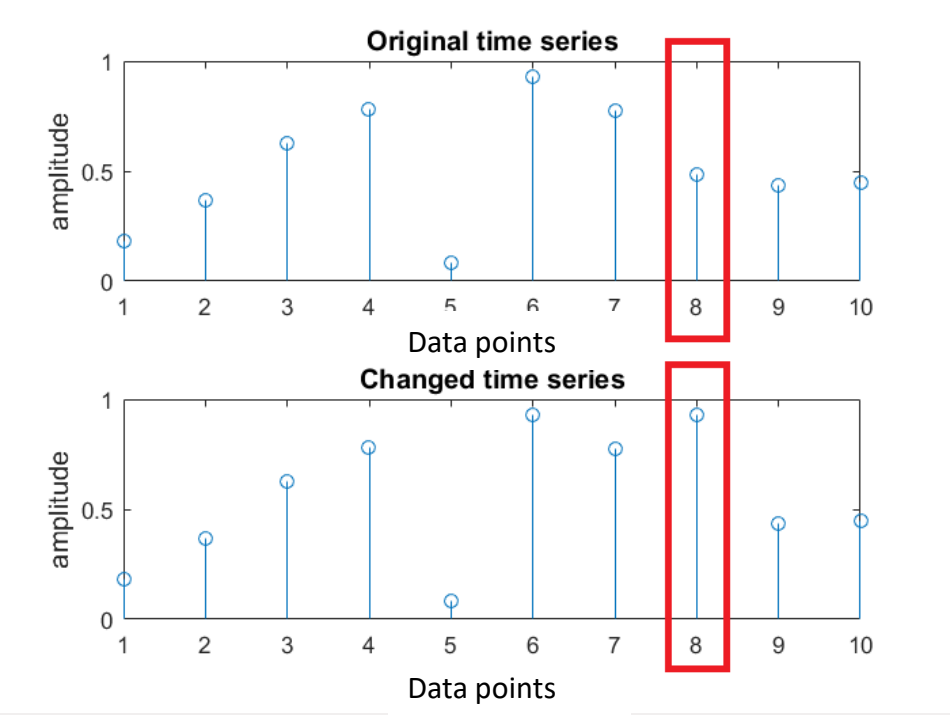
- Part Two: TVG for EEG-based nonconvulsive seizure detection.
  - EEG signals
  - Feature separability
  - Classification

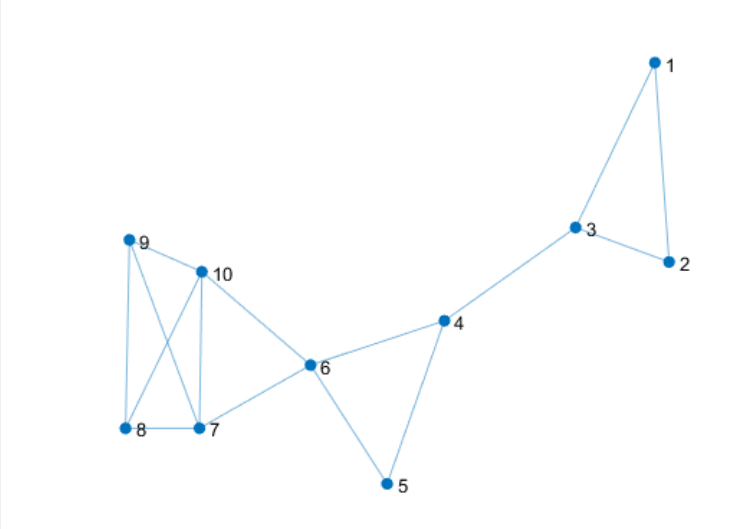
TVG

- TVG methods
- TVG trials
  - Enlarging or shrinking
  - Windowing
  - Rewiring
  - Tendency

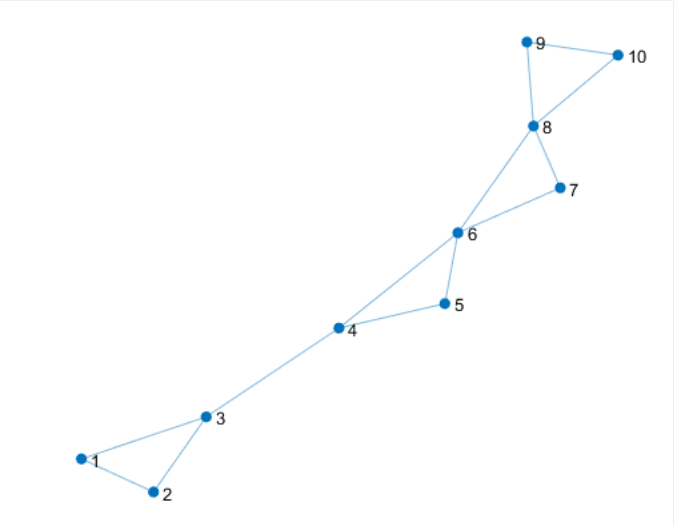
TVG trials (Enlarging or shrinking trials)

The concept of TVG trials in the first category is enlarging/shrinking different amount of random points to maximum/minimum value of the original series.





The associated BVG of the original series



The associated TVG of the original series

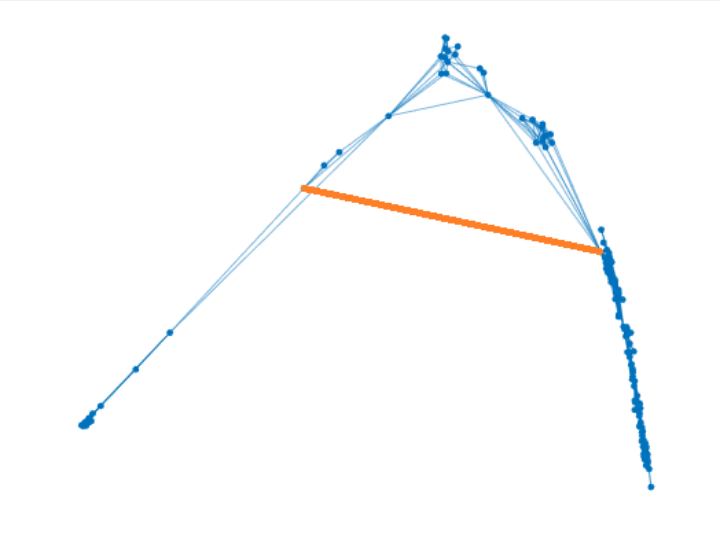
TVG trials (Windowing)

The second type of TVG trials is convolution/multiplication with different windows. For multiplication trials, only four random segments (length=4 data points) were multiplied with the artificial window.

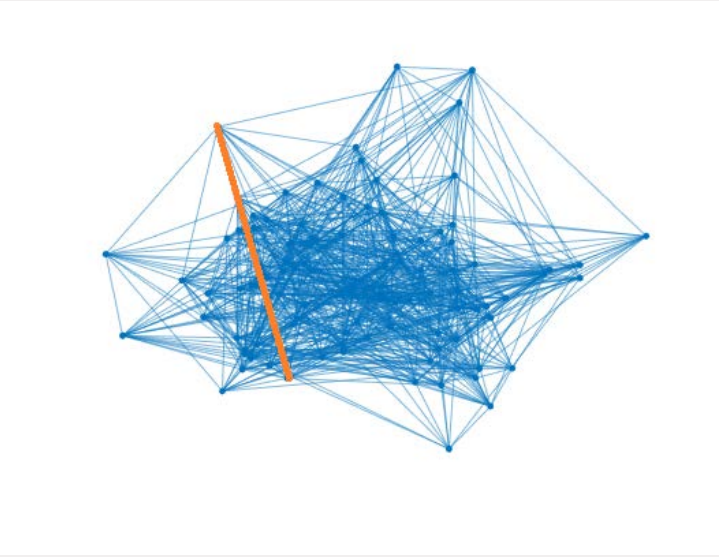
Trial No.	Convolution/Multiplication	Window
1	Convolution	[1,1,1].
2	Convolution	[1,2,1].
3	Convolution	10-point sin wave.
4	Convolution	20-point sin wave.
5	Convolution	30-point sin wave.
6	Convolution	[1,1,1,1]
7	Convolution	[1,2,2,1].
8	Convolution	[1,2,3,4].
9	Convolution	[2,1,1,2].
10	Convolution	10-point cos wave.
11	Multiplication	[0.5,0.5,0.5,0.5]
12	Multiplication	[0,0,0,0]

TVG trials (Rewiring)

The third type of TVG trials in is to connect different amount of pairs of node in VG. Each pair of node is composed of a node with a lower node degree and a node with a higher node degree.



Rewire a small-world network



Rewire a random network

TVG trials (Tendency)

To study the influence of changing different amount of random points of the time series, from one percentage to fifty percentage of the original series length were enlarged and shrunk.

Similarly, different amount of points were rewired from one percentage and fifty percentage of the original series length as well.

Part One: TVG analysis on pseudo signals

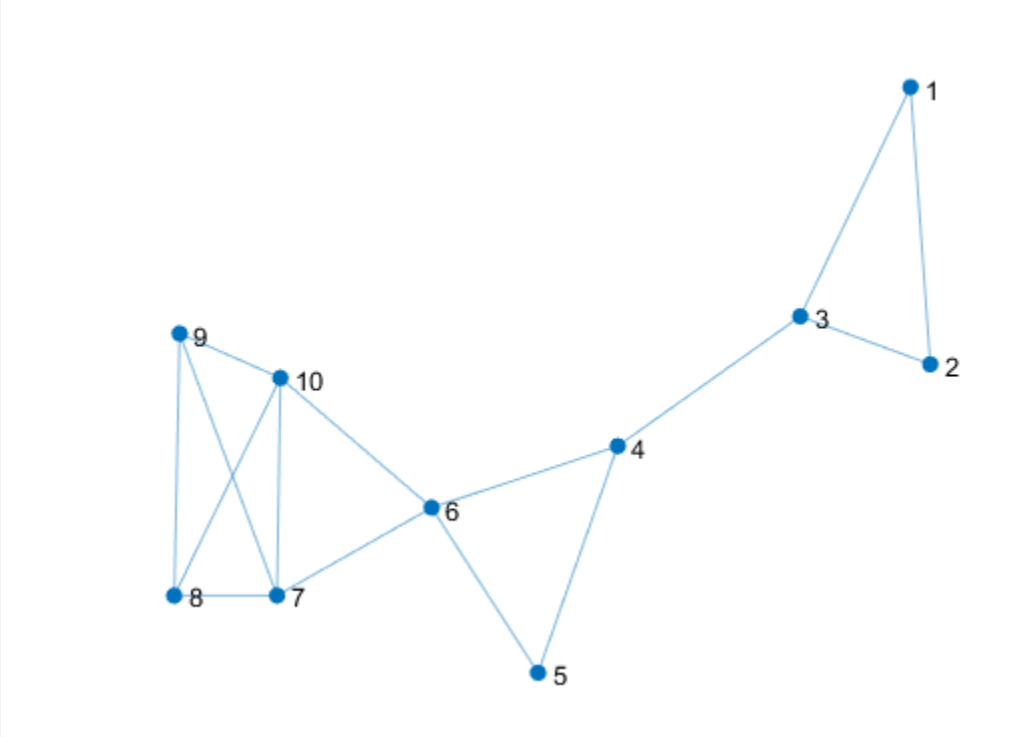
Several pseudo signals were generated as experimental data to evaluate the performance of TVG and BVG.

These pseudo signals (2500 data points each) includes:

- Two kinds of random time series
  - white noise with Uniform distribution.
  - White noise with Gaussian distribution.
- Fractional Brownian motion (FBm), with different Hurst (H) exponents
  - H=0.1, 0.3, 0.5, 0.8 .
- Two kinds of periodic time series
  - periodic white noise.
  - periodic FBm series.
- Totally, there were 8 different types of time series, each type were generated randomly by 30 times.

Characteristics of VGs

- Mean degree
- Mean path length
- Degree distribution
- Degree entropy
- Clustering coefficient
- Local efficiency
- Global efficiency
- Sample entropy
- Approximate entropy



Statistical Analysis

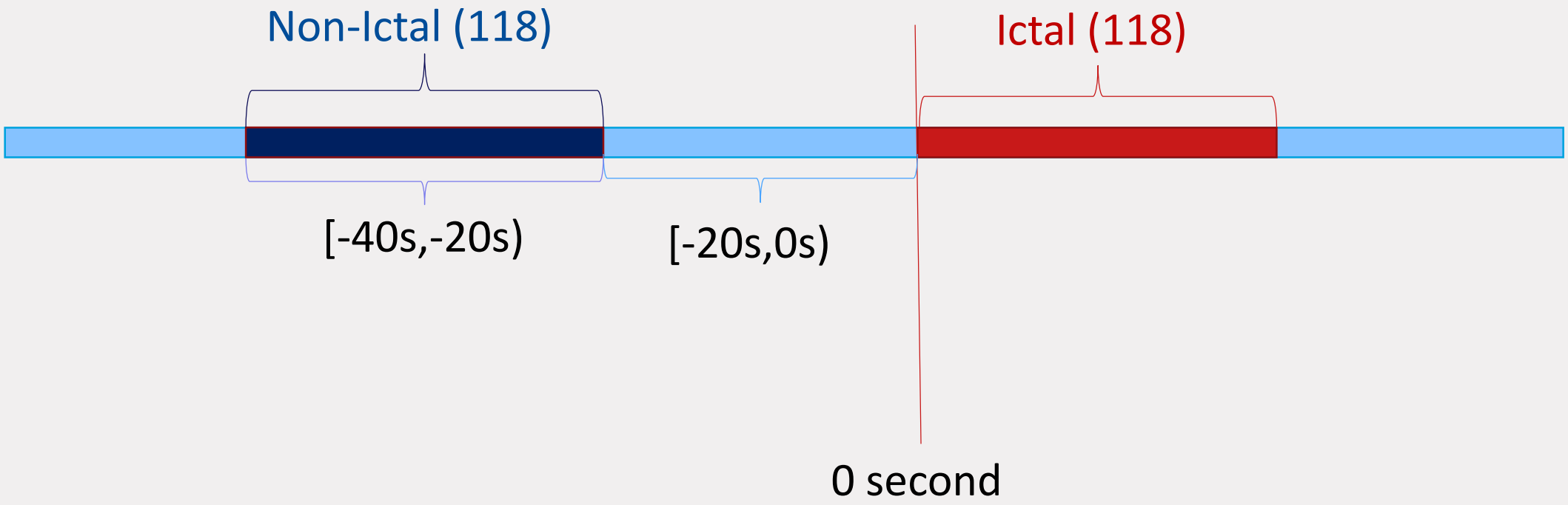
- The eight features were extracted from VGs for each pseudo signals. The features computed based on TVG trials were compared with that computed from BVG, in order to evaluate the response to changes in time series.
- Permutation test was employed.
  - The null hypothesis states that there is no difference between the TVG features and BVG features.
  - The compared result was defined to be significant if the p-value is smaller than 0.05.

Part Two:

- TVG for EEG-based nonconvulsive seizure detection.
  - EEG signals
  - Feature separability
  - Classification

EEG signals

An EEG signal from one epileptic patient was analyzed in the graph domain with BVG and TVG.



Feature separability

- In order to perform whether BVG features or TVG features can distinguish ictal and non-ictal classes, permutation test was employed.
  - The null hypothesis states that there is no difference between the features from ictal and non-ictal patterns.
- Moreover, the features extracted from BVG and TVG were compared to demonstrate the effectiveness in classifying ictal and non-ictal patterns. The Absolute standardized mean difference (ASMD) was used to evaluate features separabilibty.
  - $ASMD = \left| \frac{\mu_{ictal} - \mu_{non-ictal}}{\sqrt{\sigma_{ictal}^2 + \sigma_{non-ictal}^2 - 2\sigma_{ictal,non-ictal}}} \right|$

Classification

- A machine learning model was trained based on BVG and TVG features (extracted from EEG signals) to automatically detect ictal and non-ictal patterns.

- The same EEG recoding was segmented by a 2.56-second window.
  - Ictal (2364)
  - Non-ictal (60801)

- A RUSBoosted tree classfier
  - Imbalanced data

Results & Discussions

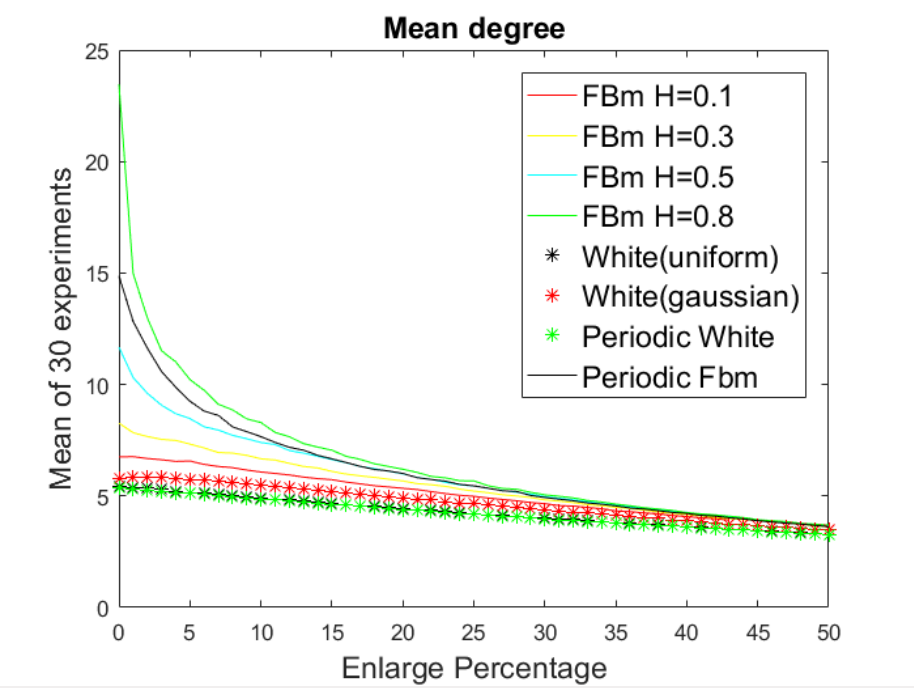
- Part One: TVG analysis with pseudo signals

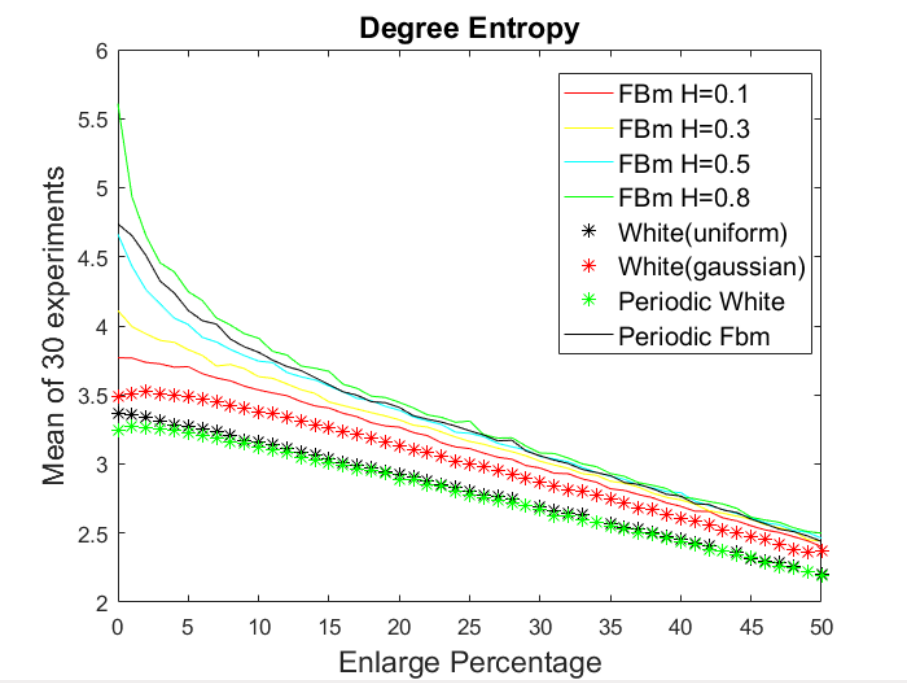
- Part Two: TVG for EEG-based nonconvulsive seizure detection

Enlarge trials

For enlarging some random points of the pseudo signals, the TVG features (compared with BVG features) present:

- MD, DE, LE and GE of different types of pseudo time series decreased.

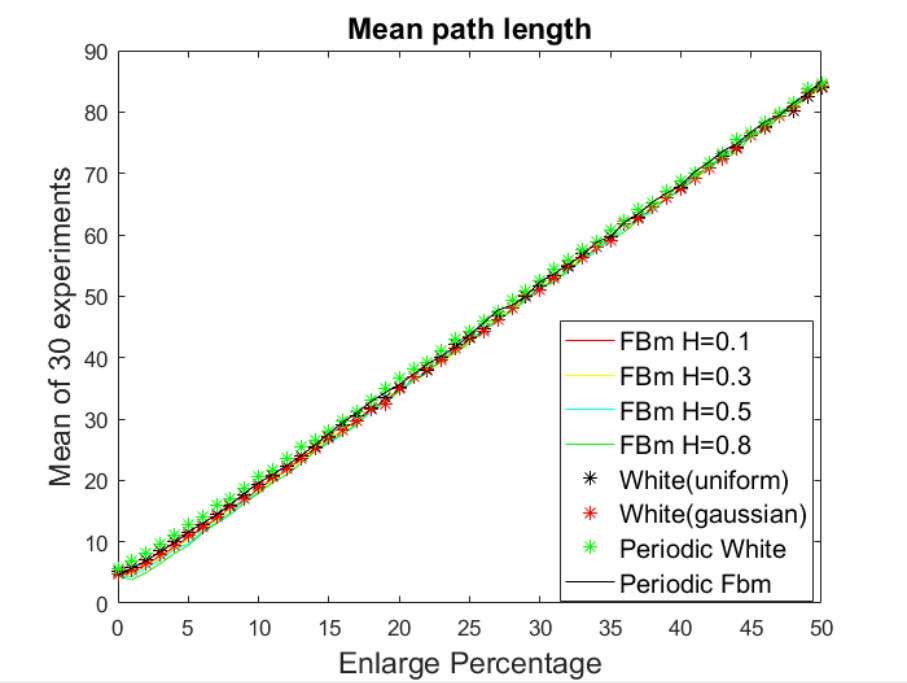




Enlarge trials

For enlarging some random points of the pseudo signals, the TVG features (compared with BVG features) present:

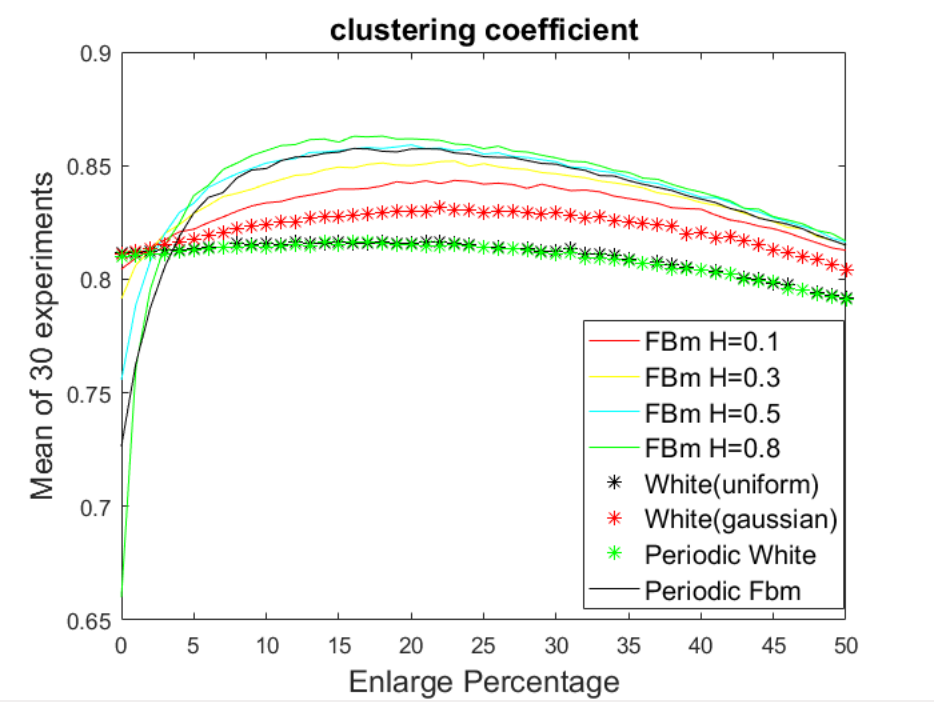
- MPL of different types of pseudo time series increased rapidly.



Enlarge trials

For enlarging some random points of the pseudo signals, the TVG features (compared with BVG features) present:

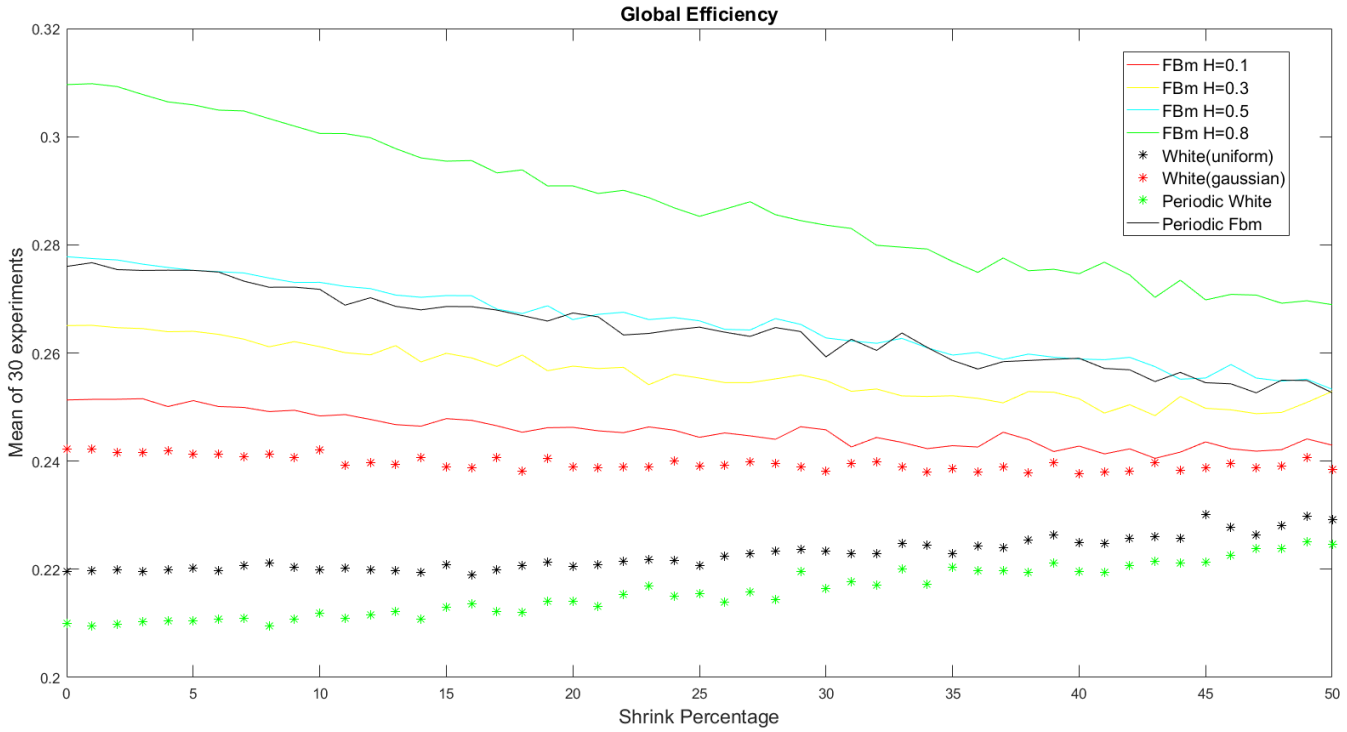
- CC, SampEn and ApEn raised at first and the diminished.



Shrink trials

For shrinking some random points of the pseudo signals, the TVG features (compared with BVG features) present:

- MD, DE, LE and GE of FBm series decreased.
- MD, DE, LE and GE of white noise series increased slightly.



Window trials

For applying window trials, the features response to two TVG trials seem contribute to distinguish different kinds of signals:

- Convolution with 10-point sin wave
- Convolution with 10-point sin wave

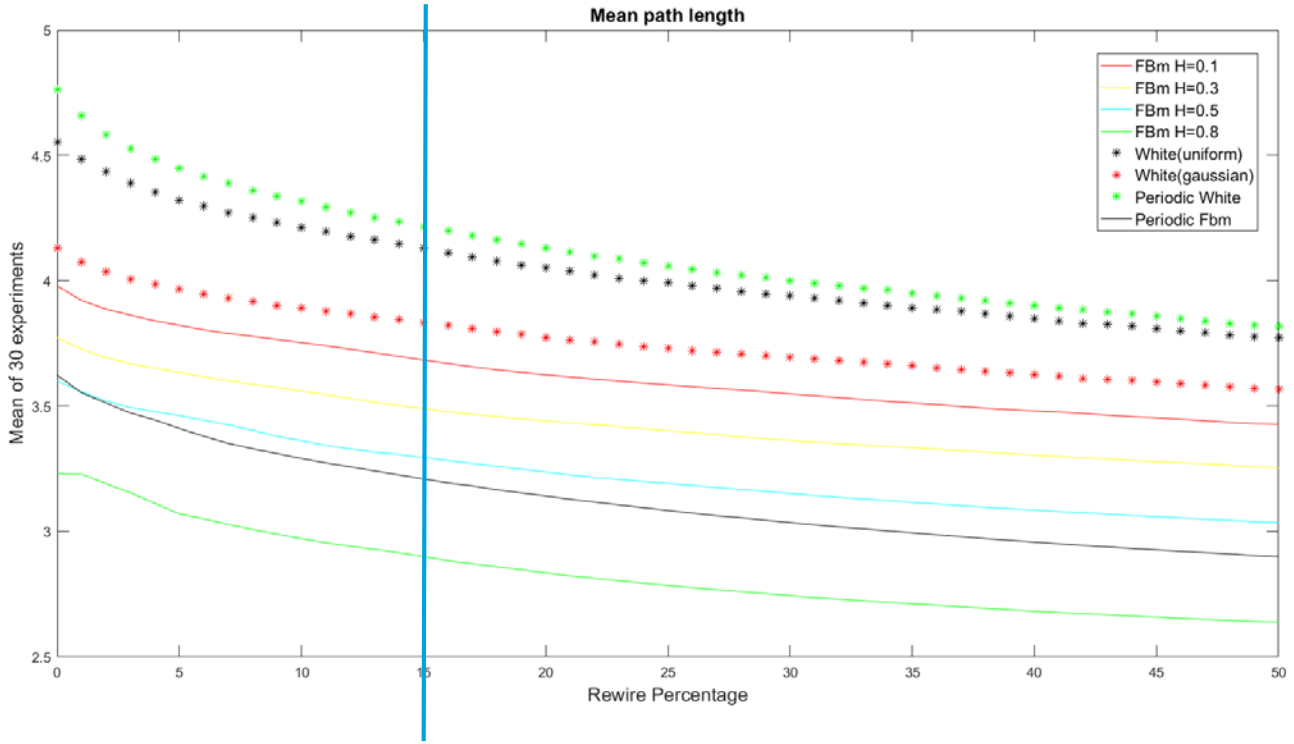
TABLE I: DE response to the TVG trial: convolution with 10-point cos wave

	DE		
Series type	BVG	TVG	P-value
FBm $H = 0.1$	3.85 ± 0.034	3.826 ± 0.033	0.001
FBm $H = 0.3$	4.27 ± 0.051	3.899 ± 0.103	0.001
FBm $H = 0.5$	5.014 ± 0.113	4.113 ± 0.193	0.001
FBm $H = 0.8$	6.912 ± 0.367	5.100 ± 0.417	0.001
White noise (uniform)	3.402 ± 0.018	3.741 ± 0.022	0.001
White noise (gaussian)	3.54 ± 0.023	3.767 ± 0.025	0.001
Periodic white noise	3.345 ± 0.045	3.65 ± 0.082	0.001
Periodic FBm	4.064 ± 0.129	3.791 ± 0.114	0.001

Rewiring trials

For rewiring trials, the TVG features (compared with BVG features) present:

- LE and CC of different types of pseudo signals decreased linearly.
- MPL and GE of different types of pseudo signals decreased stepwise.



Part One: TVG analysis with pseudo signals

In general, there are 4 TVG trials stood out for distinguishing different kinds of time series. These 4 TVG trials were defined as:

- TVG (sin): The original series convolute with 10-point sin wave.
- TVG (cos): The original series convolute with 10-point cos wave.
- TVG (shrink): Shrink 50% random points to the minimum value of the original series.
- TVG (rewire): Rewire 15% pairs of points of the original series.

TVG for EEG-based nonconvulsive seizure detection

TABLE II: ASMD between BVG and TVG methods and P-value of each methods)

Features		BVG	TVG (sin)	TVG (cos)	TVG (shrink)	TVG (rewire)
MD	ASMD	8.600	15.7	18.515	5.344	5.821
	P-value	0.001	0.001	0.001	0.001	0.001
MPL	ASMD	5.853	9.566	5.377	9.16	4.720
	P-value	0.001	0.001	0.001	0.001	0.001
GE	ASMD	5.467	9.714	4.768	9.16	4.656
	P-value	0.001	0.001	0.001	0.001	0.001
DE	ASMD	6.0312	12.013	14.46	7.945	6.105
	P-value	0.001	0.001	0.001	0.001	0.001
CC	ASMD	8.139	16.812	12.563	2.821	7.247
	P-value	0.001	0.001	0.001	0.004	0.002
LE	ASMD	8.235	16.488	12.337	2.616	7.461
	P-value	0.001	0.001	0.001	0.001	0.001
SampEn	ASMD	7.016	1.711	0.511	7.392	5.246
	P-value	0.001	0.070	0.630	0.001	0.06
ApEn	ASMD	0.2615	1.314	0.202	11.57	1.578
	P-value	0.805	0.210	0.850	0.001	0.073

Machine learning classifier

TABLE III: Classification performance

Trained data	Sensitivity	Specificity
Features from BVG	74%	57 %
Features from TVG (sin)	79%	65 %
Features from TVG (cos)	68%	65 %
Features from TVG (shrink)	74%	65 %
Features from TVG (rewire)	73%	55 %

Conclusion

The concept of our novel TVG method is that the original time series convolute with 10-point sin wave first, after which, the changed series was converted into VG by BVG method.

The features (MD,DE,MPL,CC) of TVG may help distinguish time series with different characteristics, such as white noise and FBm series.

Moreover, with a RUSBoosted trees classifier, the ictal and non-ictal classification results using the TVG features outperformed those using the BVG features.