Classification of pre-ictal states from connectivity and network measures on scalp multi-channel EEG

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Objective

The objective of this study is to discriminate late from early preictal states, on the basis of effective connectivity and network analysis on scalp multi-channel electroencephalograms (EEG). First, different Granger causality measures are computed on non-overlapping sliding windows of EEG and at each window a weighted network is formed for each Granger causality measure. Further a large number of global and node-specific network features are computed at each window. The time windows within 30 min at each state (late / early preictal) comprise the cases for the classification task, and the classification is repeated for each of the 12 epileptic episodes. Four different feature selection schemes are applied to a training set in order to find optimal feature subsets and it was found that these feature subsets classify with high accuracy late and early preictal states in a test set. Further, applying a majority vote approach the most frequent network features in the optimal feature subsets are found, which potentially may detect changes in effective connectivity prior to an epileptic seizure.

Methodology

A. EEG Data (*provided by Oslo University Hospital, Norway*)

12 preictal scalp EEG records:

- Single seizure episode of 12 patients.
- All (but one) are generalized tonic clonic (GTC) seizures.
- At least 3h and 10min duration prior to seizure onset.
- 19 channels (10-20 system) excluding frontal channels.
- Sampling time 0.01s (after subsampling)
- Filtering (high-pass at 0.3Hz, low-pass at 40Hz).
- No other data pre-processing.

Consecutive non-overlapping segments of duration 20 s (time series length = 2000)

Training and Test sets

From each EEG record two preictal states were used for classification:

- **late preictal state** (**L**): the last 30 min before the seizure onset, **totally 90 segments** of 20 s duration
- **early preictal state** (**E**): 30 min record, -2.5 h to -2 h with reference to seizure onset, **totally 90 segments** of 20 s.

From each state a subset of 70% randomly selected segments are used for training and the rest 30% for testing.
The procedure of training-testing is repeated 10 times and the accuracy indices are averaged.

B. Causality measures and Network Features

B1. Four Granger causality measures [1,2]

Representative Granger causality (GC) measures, selected to be computationally efficient, from time (1) frequency (2) state (3) and phase (4) domain are used:

(1). Restricted conditional Granger causality index, RCGCI.

(2). Restricted Generalized Partial Directed Coherence at the bands δ, θ, α, β, γ, denoted RGPDCd, RGPDCt, RGPDCa, RGPDCb and RGPDCg.

(3). Synchronization likelihood, SL.

(4). Weighted phase lag index, wPLI.

Measures (1) and (2) are the corresponding to CGCI and GPDC making use of dimension reduction (selecting a subset of terms in VAR model).

A weighted **causality network** is formed from each GC(i->j) measure computed for all (i,j) pairs, i,j=1,2,…,19, **at each segment**.

B2. Network Features [3]

A large number (379) of network measures were computed **at each causality network**, including

- global network measures (mean, std, skewness, kurtosis of the strength distribution of the weighted network, radius, diameter, centrality, transitivity Ratio, eccentricity, clustering coefficient etc.)
- the respective local (node-specific) measures.

C. Feature Selection methods [4,5]

From the initial set of 379 network features, a subset was selected to give optimal classification of L and E states in the training set. For the feature selection the following methods are used: (1) Forward Sequential Selection (**FSS**), (2) Conditional Mutual Information with Nearest Neighbors estimate (**CMINN**), (3) minimum Redundancy and Maximum Relevance (**mRMR**) , (4) Support Vector Machines with Recursive Feature Elimination **(SVM-RFE**). For SVM-RFE, mRMR and CMINN filters, the number of features in the subset is an input parameter (set to 5), while for FSS it is determined by the termination criterion. **Classification accuracy** of the feature subset is computed on the test set.

Majority vote for final feature subset: The most frequently selected features from all four feature selection methods over the 10 runs.

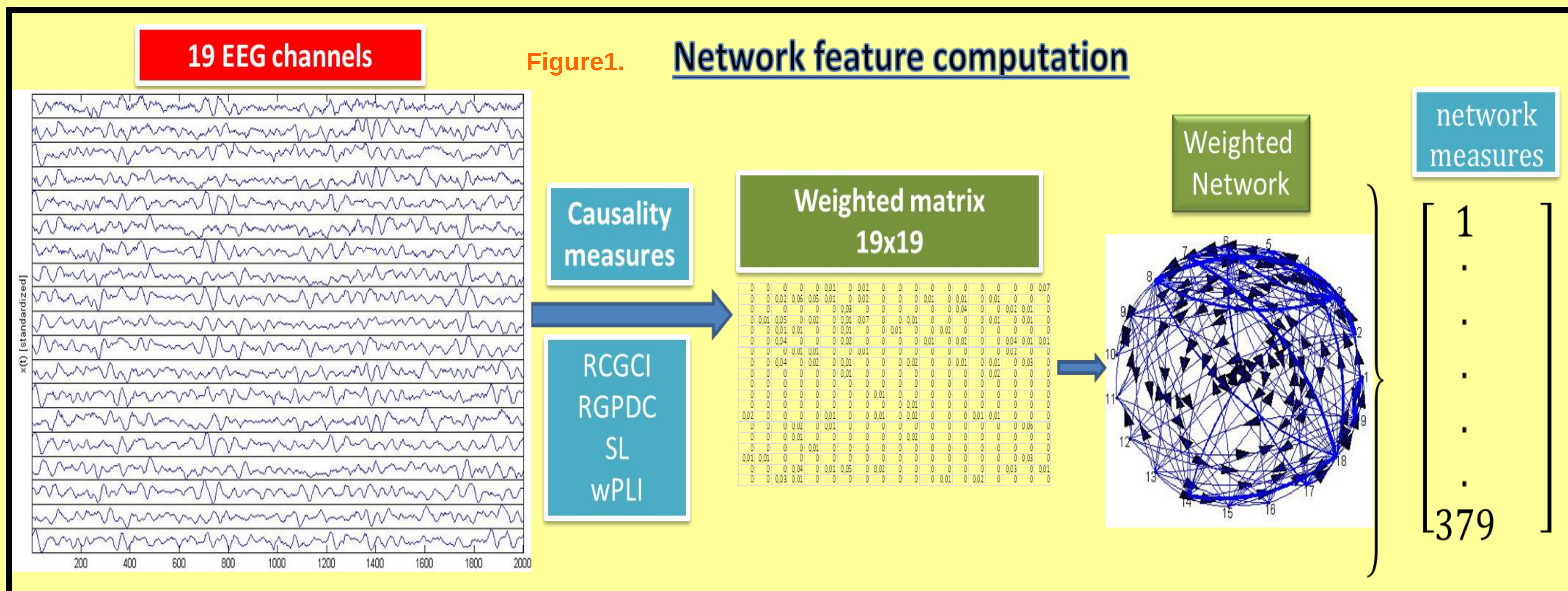


Figure1.

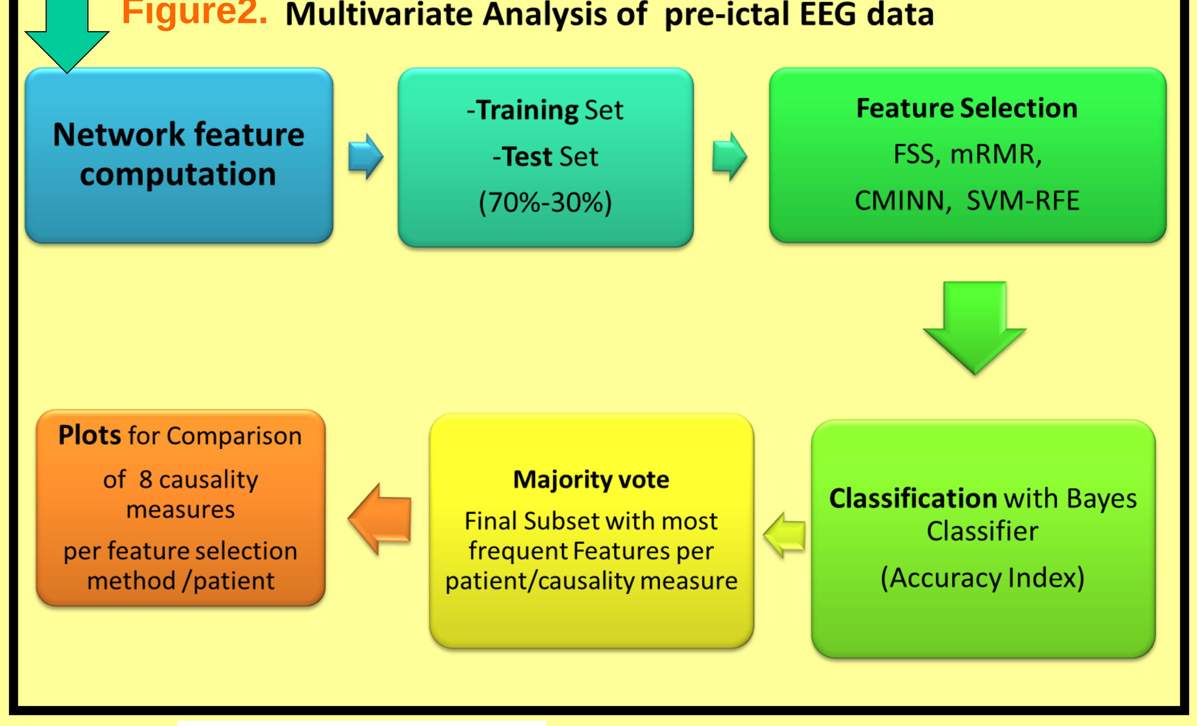
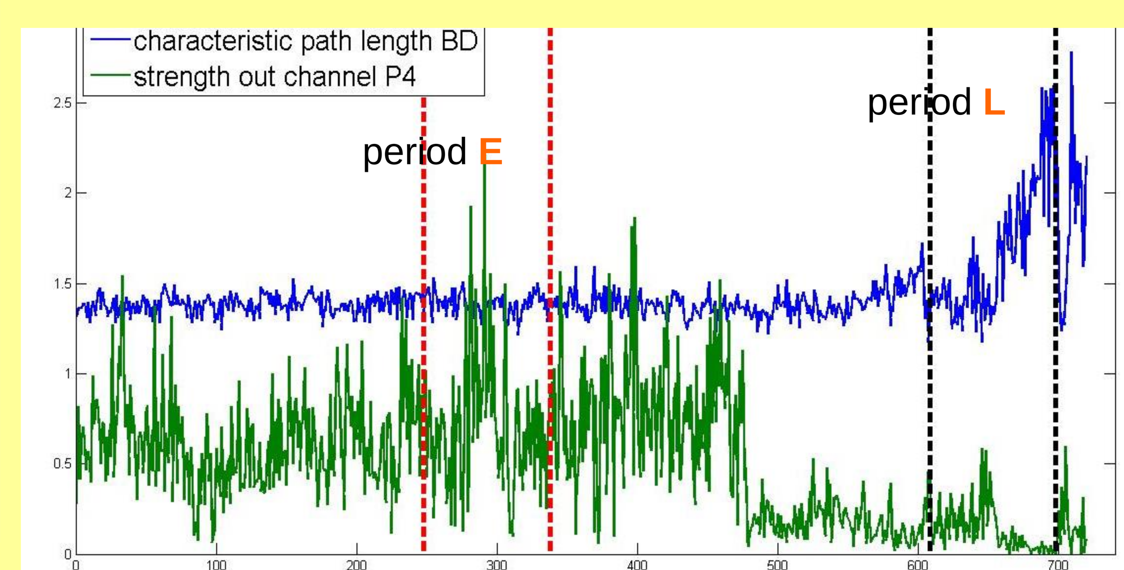


Figure2. Multivariate Analysis of pre-ictal EEG data

Figure3. Example: Profile of network features **characteristic path length BD** and **out-strength of channel P4** for the network derived by the Granger causality measure **RCGCI** for one epileptic episode. Early (E) and Late (L) preictal states are shown by vertical lines.



Results

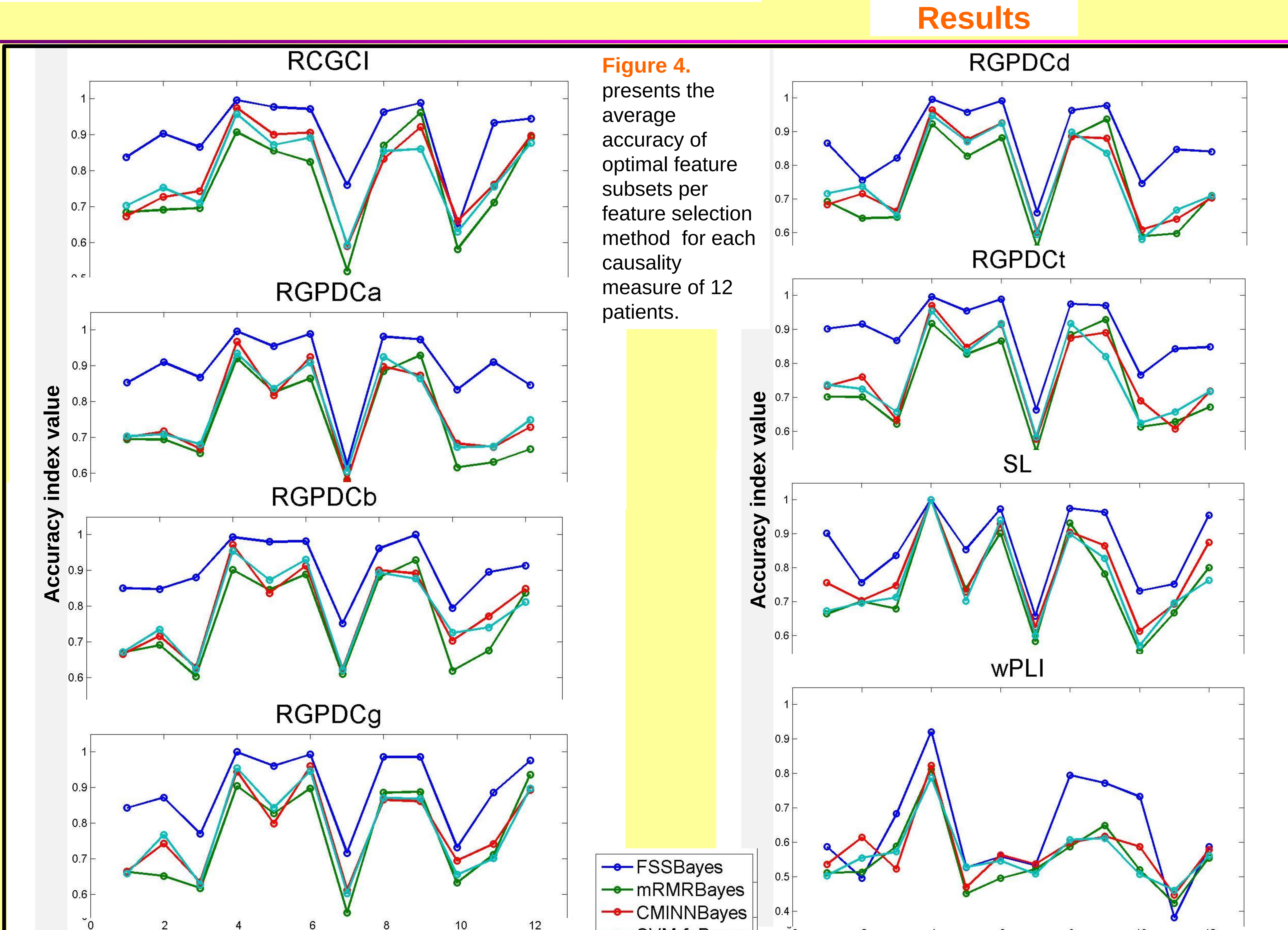


Figure 4. presents the average accuracy of optimal feature subsets per feature selection method for each causality measure of 12 patients.

Majority vote per epileptic episode for network features. Table 1 and Table 2 present network features with frequency occurrence (Freq) ≥ 20 for patient 1 and 2, respectively, for all feature selection methods and all connectivity measures.

Table 1

Feature name	Freq
strength in channel P8	75
strength out channel F9	65
strength in channel T8	35
strength channel P8	29
strength in channel F9	28
eig centr BU channel O1	26
betweenness centr WD P8	26
strength in channel C4	23
radius BD	23
local efficiency WD F9	20

Table 2

Feature name	Freq
strength in channel P8	46
strength out channel Cz	36
strength in channel Pz	32
clustering coef BD P10	29
strength channel Cz	28
betweenness centr WD Pz	28
strength channel P8	27
eig centr BU channel P8	26
strength out channel F10	26
eig centr BU channel O1	22
strength in channel T8	22
betweenness centr WD T7	21
kcs	21

Table 3

Network Feature Name	Number of Common epochs
radius BD	8
global efficiency WD	5
std eccentricity WD	6
strength in channel T8	5
strength out channel P3	5
eccentricity BD F10	6
eccentricity BD F9	5
eccentricity WD P4	6
eccentricity WD O1	5

Common network features

Table 3 presents the overall selected features. These were found in the set derived from majority vote in at least 5 of the 12 epileptic episodes.

Acknowledgement

The work is supported by the Greek General Secretariat for Research and Technology (Aristeia II, No 4822).

Conclusions

- The feature selection method FSS seems to provide feature subsets that attain the highest classification accuracy (late / early preictal states) for any of the effective connectivity measures.
- The effective connectivity measure RGPDC(beta band) gives rise to networks that tend to have different characteristics in the early and late preictal states, giving classification accuracy over 0.7 for all epileptic episodes.
- The majority vote gives a small feature subset for the discrimination of early and late preictal states.

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