Final report

Estimation of coupling between brain and heart systems

(with applications to sleep stages scoring)

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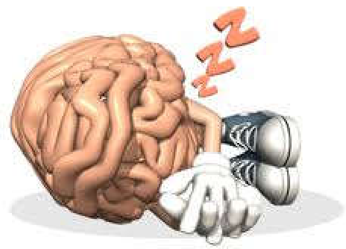
Outline

- About sleeping brain
- Sleep scoring & problem statement
- General approaches to evaluation coupling between brain and heart systems
- Measures
  - Synchronization Likelihood
  - Mutual Information
  - Phase Synchronization
- Conclusions and Future work

Due to lack of time – less about recent results on HRV sleep scoring (there is no one), less background, less introduction, less overview of references, more results and open problems.

Introduction



Sleeping Brain

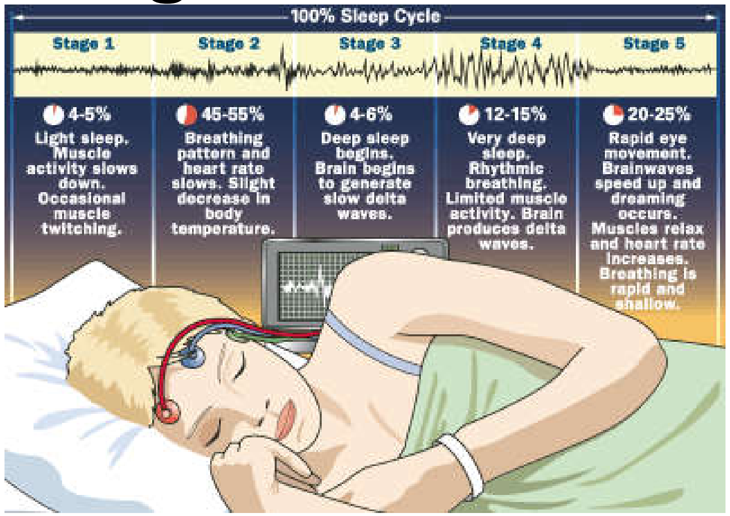
Sleep is as ancient as life itself.
We spend one third of our life sleeping.
*The question about **why, how and for what** we sleep is still far from final solution.*

Sleep is a naturally recurring state characterized by reduced or absent consciousness, relatively suspended sensory activity, and inactivity of nearly all voluntary muscles.

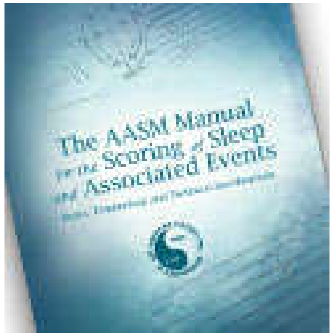
Theories of sleep:

1. **Deafferentation theory** – sleep is caused by decrease of effective sensor stimulation of the brain.
2. **Reticular theory** – reticular formation in the brainstem is to sustain brain activity needed for wakefulness.
3. **Serotonin theory** – producing more serotonin in the brain sutura nuclei causes the sleep onset.
4. **Endogenic sleep-factors** – the presence of some glycopeptides causes sleep.

Sleep Stage Scoring



Until 2007, sleep was scored according so-called “R&K rule”, came from the Allan Rechtschaffen and Anthony Kales sleep scoring manual of 1968.
Now there is new ***American Academy of Sleep Medicine Manual for Scoring Sleep and Associated Events.***



New manual provides rules not only for scoring sleep stages but also for scoring arousals, respiratory events during sleep, movements during sleep and cardiac events

Sleep stage scoring is a rule-based neurophysiology test requiring an understanding of the basic mechanisms underlying the generation of **cephalic electric potentials** coupled with **eye movements** and **muscle signal**.

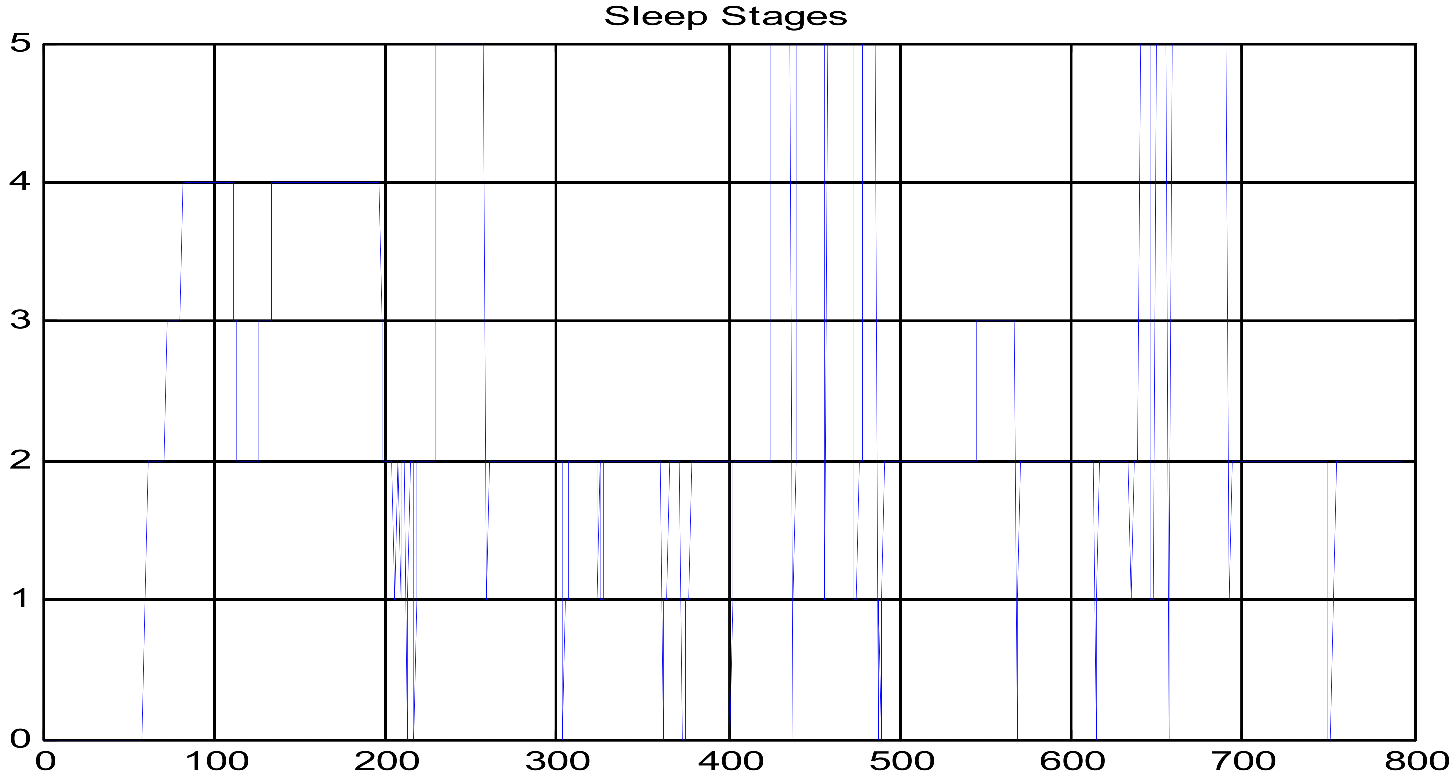
Signals of interest are generated from the brain (ie, cortex and deeper structures) and the facial muscles (ie, signals picked up by periorbital and submental electromyographic [EMG] leads).

http://www.aasmnet.org/store/product.aspx?pid=176

Sleep Stages-1

Nocturnal sleep is subdivided into cycles, and each cycle repeats 4-5 times during the night. Each cycle consists of a cascade of sleep stages, normally of the same order of occurrence, but with different proportions during the night.

Normal human sleep is comprised of two distinct stages:
-non-rapid eye movement (**NREM**) sleep;
-rapid eye movement (**REM**) sleep.

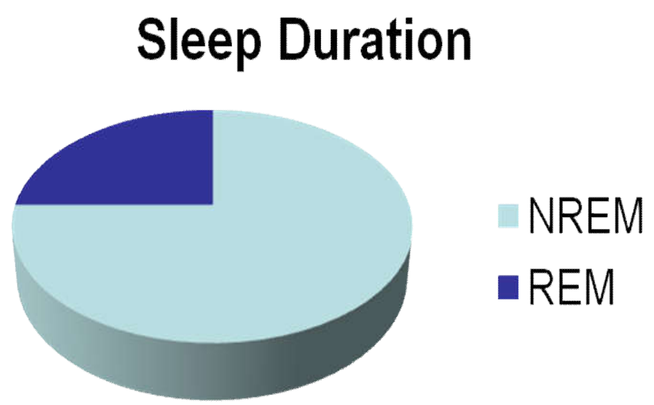


Sleep Stages-2

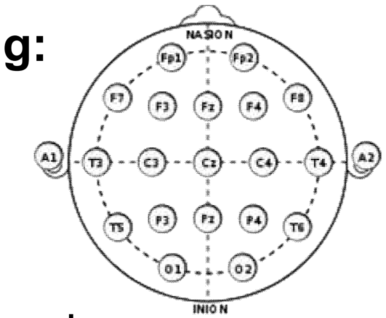
NREM sleep is subdivided into 3 stages, numbering from **N1** to **N3**
REM sleep can be subdivided into **phasic** and **tonic** sleep

Tonic REM sleep – desynchronized EEG, atonia of skeletal muscles groups, suppression of monosynaptic and polysynaptic reflexes.

Phasic REM sleep – rapid eye movements in all directions, transient swings in blood pressure, heart rate changes, irregular respiration, tongue movements, myoclonic twitching of chin and limb muscles.



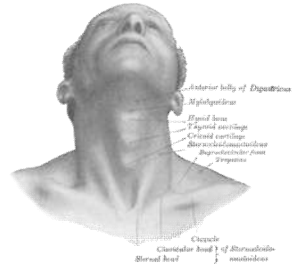
Sleep Stages-3



Minimal EEG technical requirements include the following:

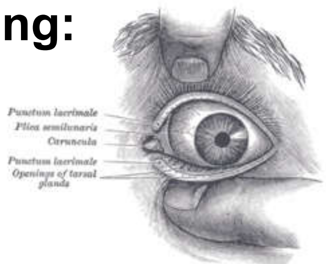
- left and right centrocephalic electrodes (C3, C4);
- left and right occipital electrodes (O1, O2);
- left and right frontal leads (F3, F4).

All active leads are referenced to electrodes on the opposite right and left mastoid processes (M2, M1).



Minimal EMG technical requirements include:

3 chin EMG electrodes; 2 are used throughout the study with the additional lead used as a backup.



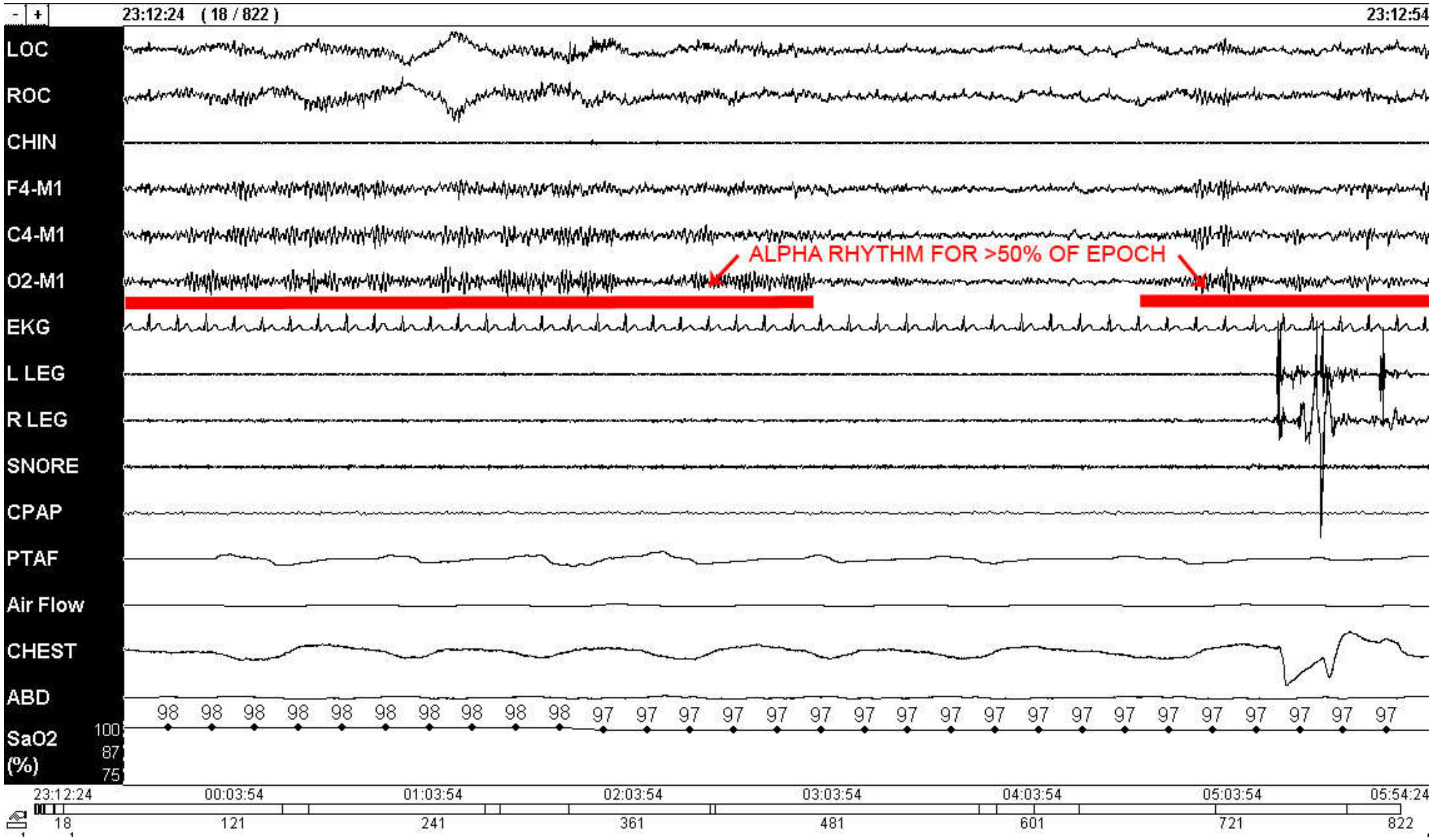
Minimal EOG technical requirements include the following:

One lead placed 1 cm below the left outer canthus
One lead placed 1 cm above the right outer canthus

Wakefulness

During normal wakefulness with closed eyes, the posterior dominant rhythm (PDR) is detected over the occipital leads. It is a sinusoidal rhythm with a frequency of 8.5-13 Hz, roughly the range of alpha frequency, and thus is also called the alpha rhythm.

Stage W is scored when there is alpha rhythm in greater than 50% of the epoch.

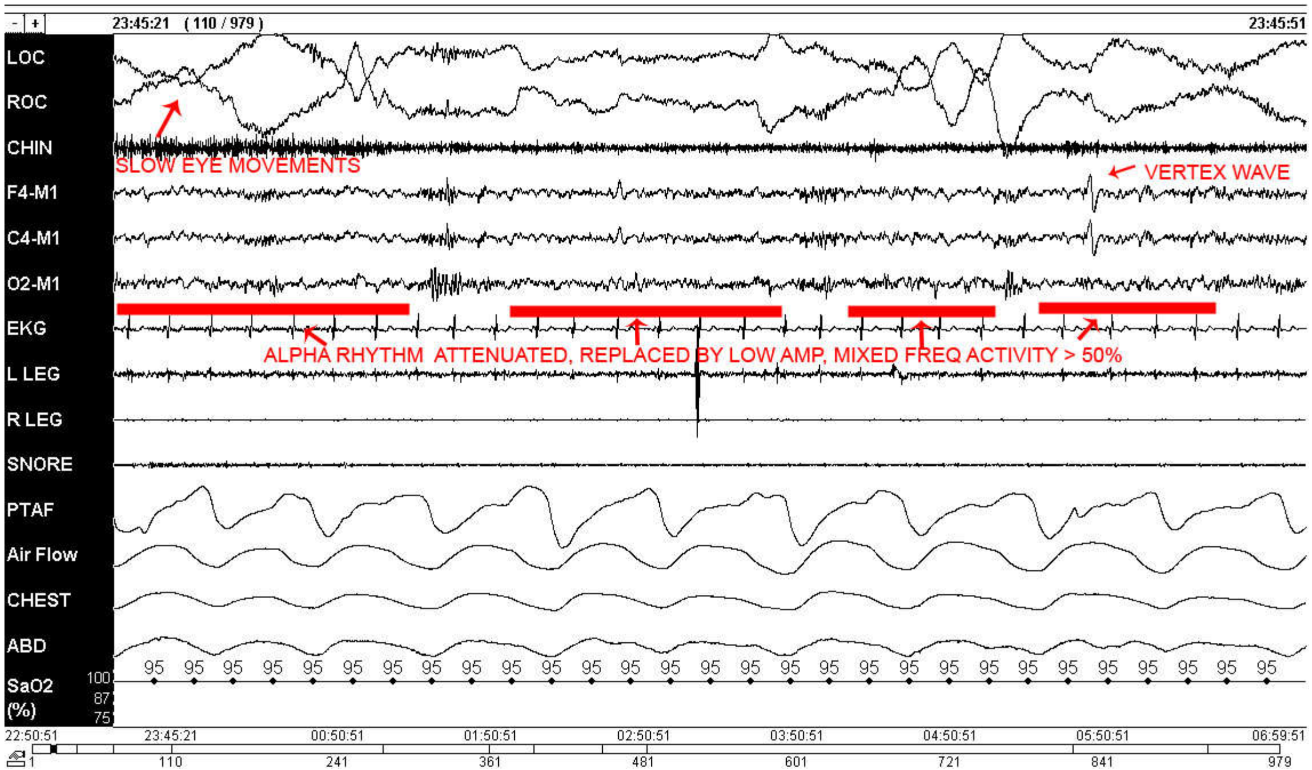


http://emedicine.medscape.com

Stage N1

Sleep onset is defined as the first stage of the polysomnogram scored other than stage W. Stage N1 is scored when alpha rhythm is attenuated and replaced by low amplitude, mixed frequency for more than 50% of the epoch stage N1 may be scored based on the presence of the following:

- Vertex sharp waves, which are prominent sharply contoured negative waves lasting < 0.5 seconds and maximal over the central region;
- Slow, rolling eye movements, detectable on EOG;
- Activity in the range of 4-7 Hz with slowing of the background frequencies of the EEG by 1 Hz or more when compared with stage W.



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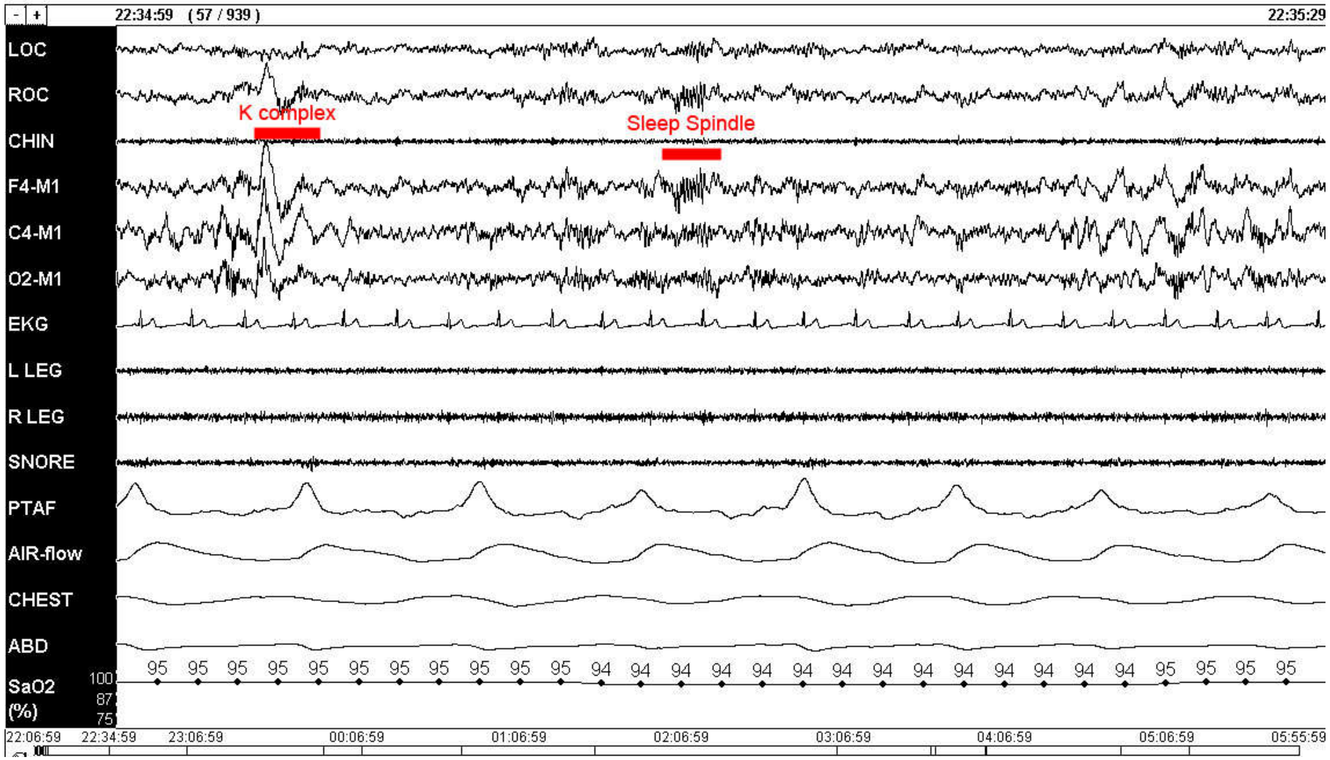
Stage N2

Stage N2 is characterized by the presence of sleep spindles and K complexes on a background of low-amplitude, mixed frequency activity.

- Sleep spindles are bursts of waves, named according to their shape. They are seen maximally over the central leads, have a frequency of 12-16 Hz and last 0.5 seconds or longer (see image above).
- K complexes have an initial negative wave, followed by a positive wave. They are clearly different than the background and last 0.5 seconds or longer. They are usually maximally seen over the frontal derivations.
- K complexes are also seen with arousals.



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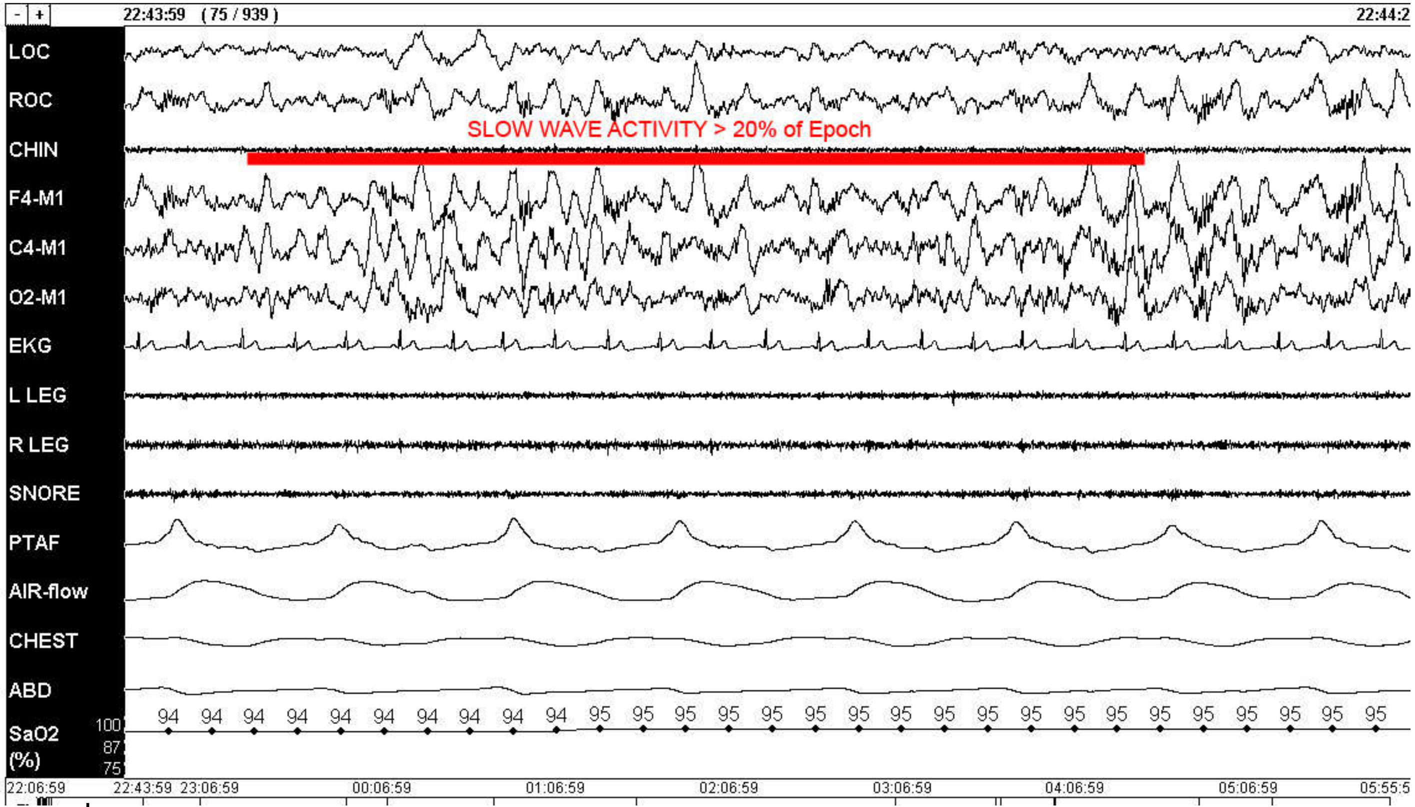
Stage N3

(former R&K stage III and stage IV)

Stage N3 is scored when there is slow wave activity in greater than 20% of the epoch. Slow waves are defined as waves with a frequency of 0.5-2 Hz and amplitude of 75 microvolts peak to peak when measured over the frontal region.

Although not required for scoring, sleep spindles may persist in stage N3 sleep. Eye movements are unusual in this stage. While variable, chin EMG tone is often low, sometimes as low as in stage R.



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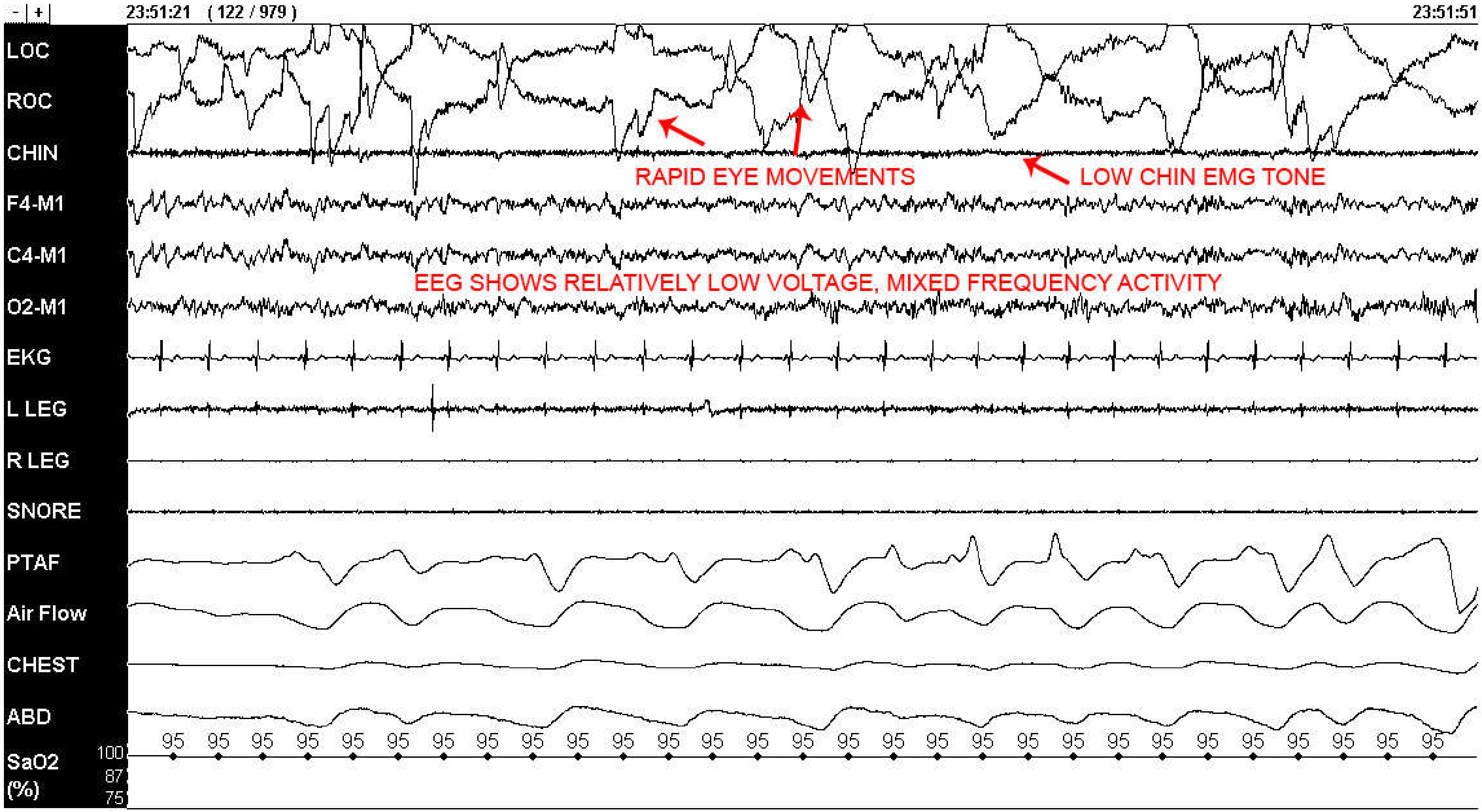
Stage R

Stage REM is scored when the following occur:

-The EOG leads demonstrate REMs, which are irregular, conjugate, sharply peaked eye movements with an initial phase lasting less than 500 msec;

-The EEG shows relatively low-voltage and mixed-frequency activities and may resemble the EEG of stage N1 or the slow alpha activity of stage W;

- Chin EMG tone is at the lowest of any stage in the polysomnogram.



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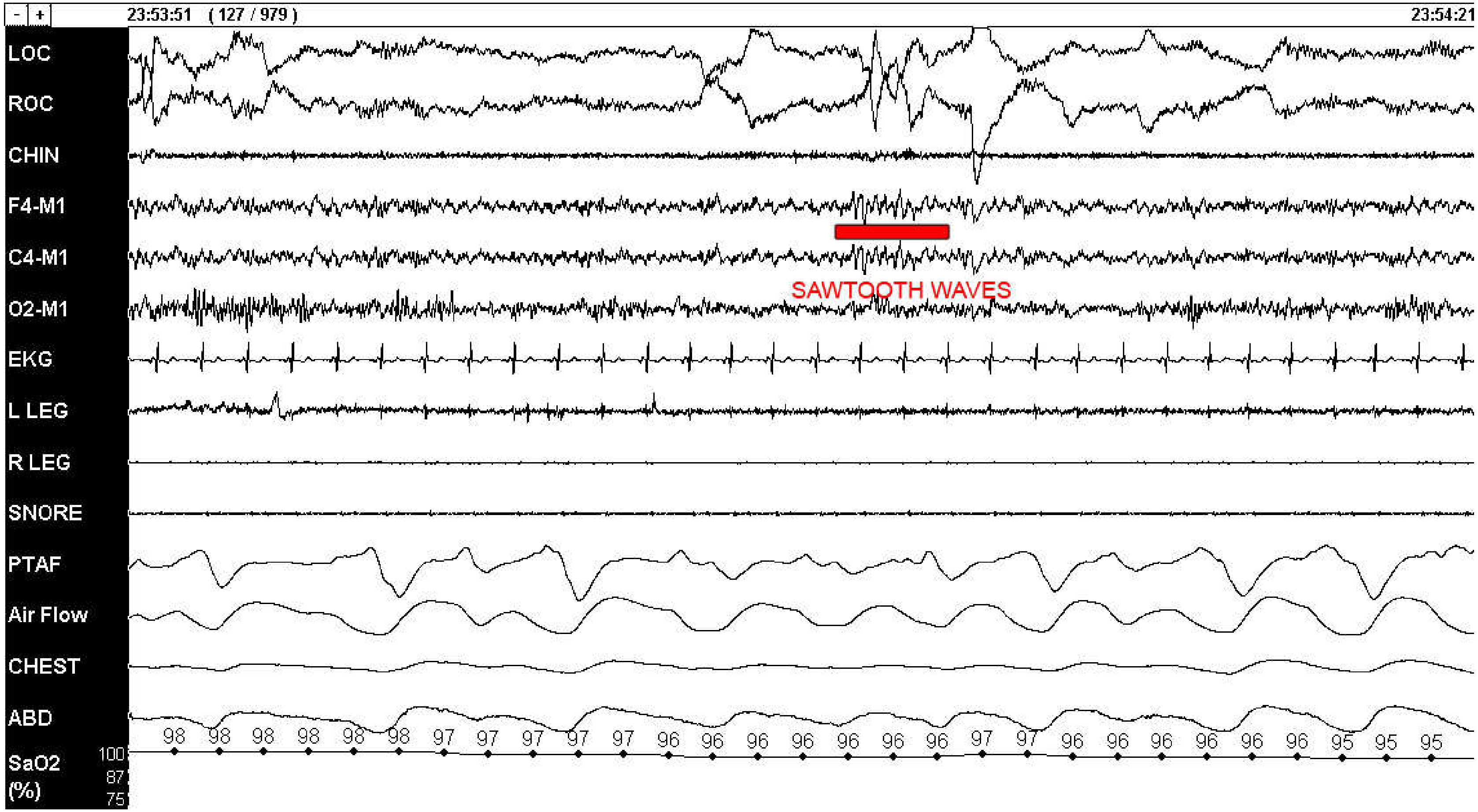
Stage R

Polysomnographic features that are supportive but not required in stage R include sawtooth waves and phasic muscle twitches. Sawtooth waves are 2-6 Hz serrated bursts of activity maximal centrally that precede REMs. Phasic muscle activity are bursts of EMG activity lasting less than 0.25 msec and may be detected on chin EMG, anterior tibialis, or EOG-EEG leads.



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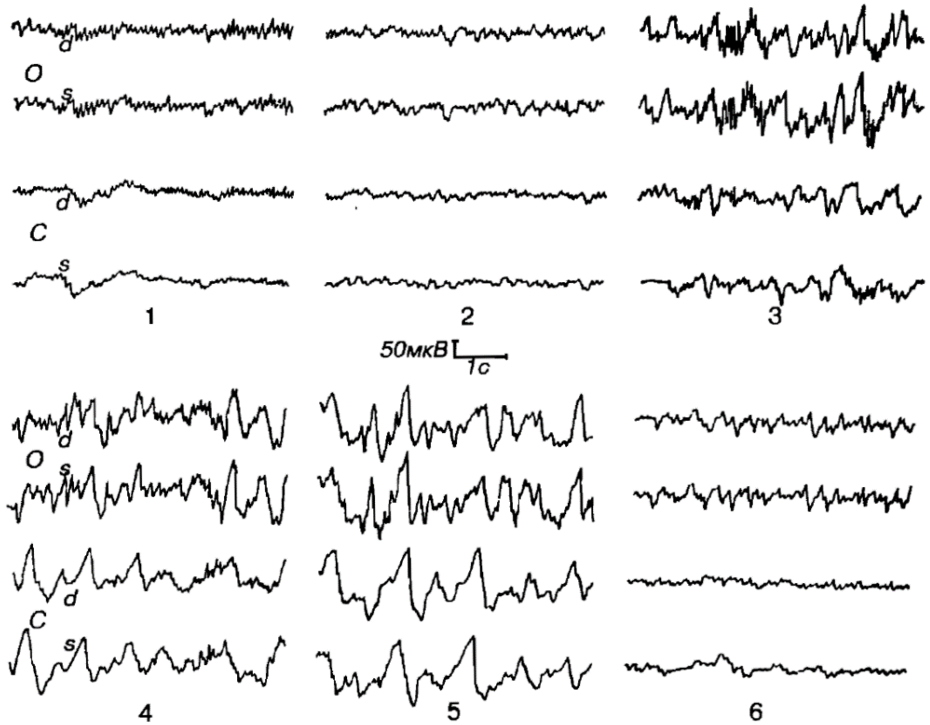
Brain activity during sleep

Sleep is known to be a dynamic state of consciousness that is characterized by rapid fluctuations in autonomic activity controlling coronary artery tone, systemic blood pressure, and heart rate.

Brain during Sleep

- Operates without stabilization influences as when awaken.
- Pre-frontal cortex during REM is minimally activated, brain operates with diminished self-reflection.
- Reduction of neuromodulatory inhibition during REM is observed.

The network of cell groups activates the thalamus and cerebral cortex during wakefullnes. Hypothalamus shuts off this arousal system during sleep.



Heart activity during sleep-1

During sleep brainstem cardiovascular controllers are under minimal influences originating not only from external but also internal environments of a body, such as:

-**Higher cortical functions;**
-**Thalamocortical;**
-**Reticular activation and**
-**Limbic system.**

The results on neural mechanisms responsible for heart rate variability during sleep are still conflicting.

During sleep:

- vagal (parasympathetic) activity is high and sympathetic activity is relatively quiescent. Although the phasic bursts of rapid eye movements characteristic of REM sleep may reflect sympathetic activation;
-parasympathetic NS prevails during NREM, sympathetic – during REM;
-HR and BP increases;
-Respiratory sinus arrhythmia increases.

Heart activity during sleep-2

Fourier spectral analysis is used mainly for differentiating sleep stages. The results are sometimes conflicting.

-While falling asleep total power as well as HF and LF decreases;
-During NREM **HF** component increases while **LF/HF** ratio decreases;
-During deep NREM HF rises and LF becomes weak;
-During REM **HF** decreases while **LF/HF** increases;
-During deep sleep peak in the power spectrum of HRV is present, indicating vagally mediated respiratory sinus arrhythmia;
-VLF component is large during REM and low during NREM;
-LF and HF components are the functions of sleep and do not reflect either time asleep nor circadian system influences.

We have also be aware that the characteristics of HRV dynamics during sleep may be caused by:

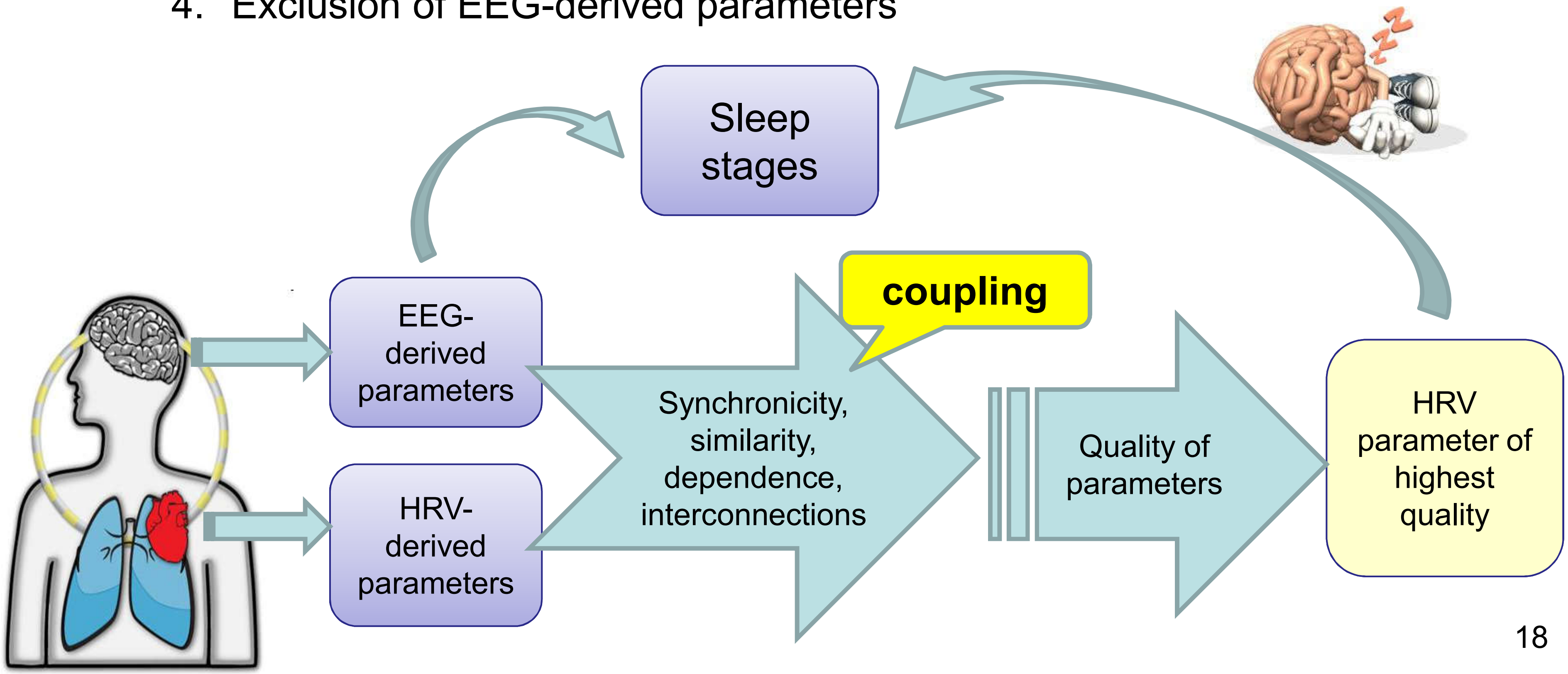
-Decreasing of ventilation;
-Decreasing of rate and variability of breath function;
-Changing of breathing mechanics;
-Decreasing of baroreflector sensitivity and reactivity;
-Changing of blood gases content.

Using HRV instead of EEG

How to use measures of coupling for sleep scoring by HRV parameters?

Assumptions

1. Correct sleep (and sleep stages) scored by medical doctor.
2. EEG-derived parameters, reflecting the sleep stages
3. HRV-derived parameters, which changes synchronously with EEG-derived parameters.
4. Exclusion of EEG-derived parameters

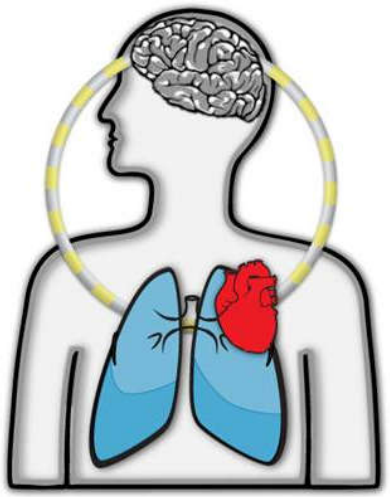


Sleep and sleep scoring

Heart and brain systems are obviously coupled, and the question is how deeply and in what way they influence each other.

Between brain and heart systems there are anatomical and functional connections and interactions, thus such approach is eligible for use.

We need to investigate and prove the mode of interactions between two systems at different levels and characterize it with quantitative parameter(s).



To understand functional connectivity between heart and brain we might need to estimate also coupling direction between these two systems.

Plan of the work

1. Obtaining previously calculated EEG and HRV parameters.
2. Selection of coupling measures which might be useful for estimating linear and nonlinear coupling between heart and brain activity.
3. Studying theoretical background of selected techniques, finding the best appropriate parameters for calculations.
4. Implementation of calculation routine in MatLAB, testing on standard signals.
5. Developing quality measures for estimation of coupling between heart and brain parameters.
6. Calculation of quality measures and making conclusions.
7. Stating open problems and derivation of directions for further work.

Data

All data are from SIESTA database, the pairs of two signals were composed for synchronicity evaluation.

1. Ten EEG parameters:

Delta
Theta
Alpha
Beta
Beta/Delta
Beta/Theta
Beta/Alpha
Alpha/Delta
Alpha/Theta
Theta/Delta

2. Forty-five ECG parameters:

22. meanNN	6. FWRENYI4	57. HFn
32. Shannon	36. pNNI10	56. LFn
35. renyi2	4. FWSHANN	44. XF
33. renyi025	5. FWRENY25	42. LF
24. cvNN	3. FORBWORD	48. LFtoHF
23. sdNN	54. UV_LFtoP	49. LFtoP
34. renyi4	51. VLFtoP	30. pNN100
38. pNNI30	9. WPSUM13	58. noNNtime
39. pNNI50	47. P	13. PHVAR20
28. rmssd	45. YF	8. WPSUM02
53. allLFtoP	7. WSDVAR	12. PLVAR20
25. sdaNN1	46. ZF	31. pNN200
29. pNN50	43. HF	14. PHVAR50
37. NNI20	55. UVLF	11. PLVAR10
50. HFtoP	41. VLF	15. PHVAR100

Assumptions-1

1. **Cooperation** between two systems can be described by various forms of **synchronization** and/or **directional influence**:
   - Generalized (lag) synchronization;
   - Phase synchronization;
   - Drive-response synchronization;
   - Bidirectional influence.

2. Most of techniques estimate only the strength of synchronization, but some of them can infer the synchronization direction.

Synchronization between two systems can be regarded as **adjusting** some of their **time-varying properties** to a common behavior due to coupling or external forcing.

General synchronization is when a state of *response* system Y is a (non-)linear function of the state of *driver* system X.

Assumptions-2

3. From the point of view of the Theory of signals and systems we face the classic case of **Bivariate analysis**, while there are dealing only with two signals, each from one of two systems.

As initial data the preliminary calculated set of parameters will be used (SIESTA dataset, 95 linear and nonlinear measures of EEG and HR, derived from the PSG signals):

Entropy, HRV time and frequency characteristics,
EEG frequency bands power…

4. We will concentrate mostly on **nonlinear** measures of coupling between two systems, based on available parameters.

Assumptions-3

5. **Synchronization Likelihood**

– detects linear and nonlinear dependencies between two signals. Relies on detection of simultaneously occurring patterns which can be complex and widely different in two signals.

6. **Mutual Information**

– indicates the amount of information about variable X we obtain by knowing Y and vise versa.

This measure can be asymmetric, defining the driver-response interactions between two systems.

7. **Phase Synchronization**

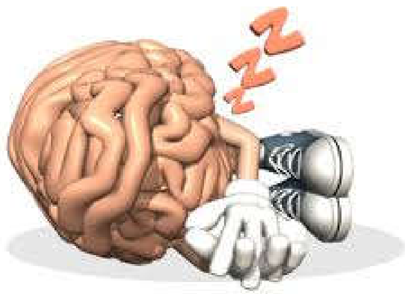
– allows to quantify frequency-specific synchronization (transient phase-locking) between two signals.

This measure can be used to estimate direction of coupling. Although it is mostly used for periodic oscillatory processes, it is worth to try it for the narrow-band components of the signals.

Another approaches

1. Granger causality – measures how the history of one signal predicts the future of another time series. But it cannot be applied to non-linear time series models.
2. Transfer Entropy
3. Permutation analysis and CMI
4. Evolution map approach and Instantaneous period approach – they use instantaneous phases and hence are sensitive to noise and nonstationaries.
5. State-space approach – requires optimal embedding parameters
6. Phase-dynamic approach – requires strong oscillatory behavior.
7. Minimum description length – measures dependence between time series by predictability of each of two series from another.

Synchronization Likelihood



Synchronization Likelihood-1

The measure which detects linear and nonlinear dependencies between two signals. Relies on detection of simultaneously occurring patterns in two signals.

Main advantages:

– it varies between 0 and 1, “0” means no synchronization,
“1” means perfect synchronization.

– patterns can be complex and widely different in two signals, which is extremely suitable for analyzing signals from different origins and of different nature.

SL could be used for selecting the pairs of signals, one from brain, another from heart, which are in closest connection. These signals could be first candidates to use for sleep stage scoring.

Synchronization Likelihood-2

Theoretical Background

1. Constructing the state embedded vectors for representation of system dynamics.

$$X_{k,i} = (x_{k,i}, x_{k,i+l}, x_{k,i+2l}, \ldots, x_{k,i+(m-1)l})$$

k – channel (signal) number
i – sample number
l – time lag
m – embedded dimension

2. Defining the probability that embedded vectors are closer than predefined distance to each other.

$$P_{k,i}^{\varepsilon} = \frac{1}{2(w_2 - w_1)} \sum_{\substack{j=1 \\ w_1 < |i-j| < w_2}}^{N} \theta(\varepsilon - |X_{k,i} - X_{k,j}|)$$

ε – distance between the embedded vectors
w_1 – correction window to avoid correlational effects
w_2 – window for sharpening the time resolution
θ – Heaviside step function

Synchronization Likelihood-3

Theoretical Background

3. For each channel *k* and each time instance *i* critical distance P_{ref} between embedded vectors is defined

$$P_{ref} << 1$$

4. Determination for each time instance *i* the number of simultaneous occurrences in two signals, when the embedded vectors are closed then P_{ref}.

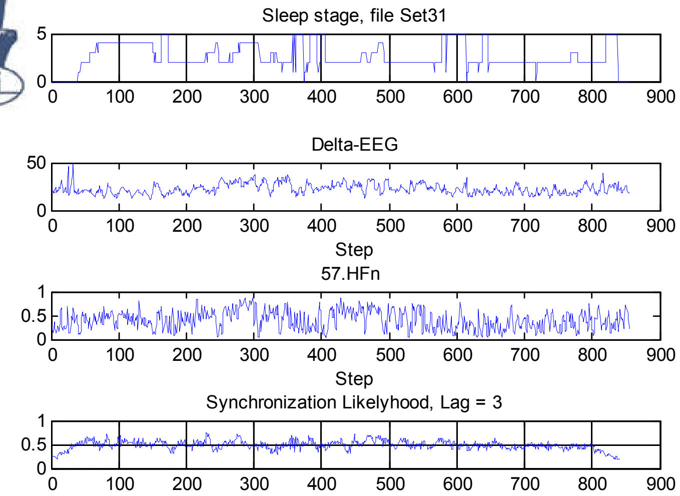
5. The ratio of the number of simultaneous occurrences to total number of embedded vectors is Synchronization Likelihood for the time *i*.

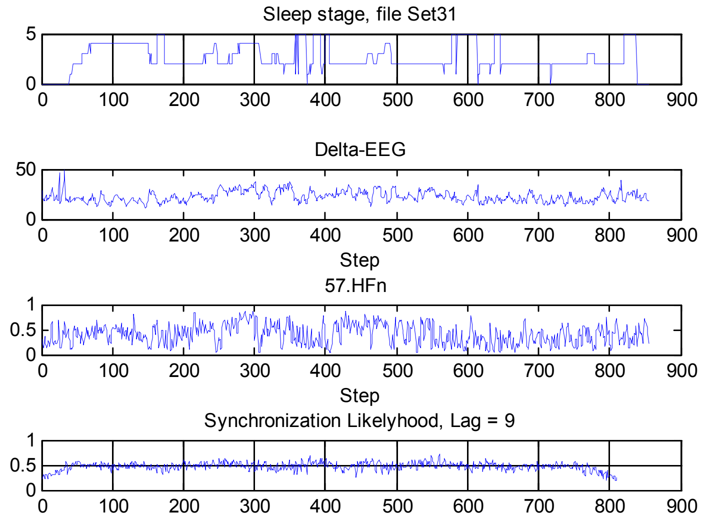
$$SL = \frac{number\ of\ embedded\ vectors\ closer\ than\ \varepsilon}{total\ number\ of\ embedded\ vectors}$$

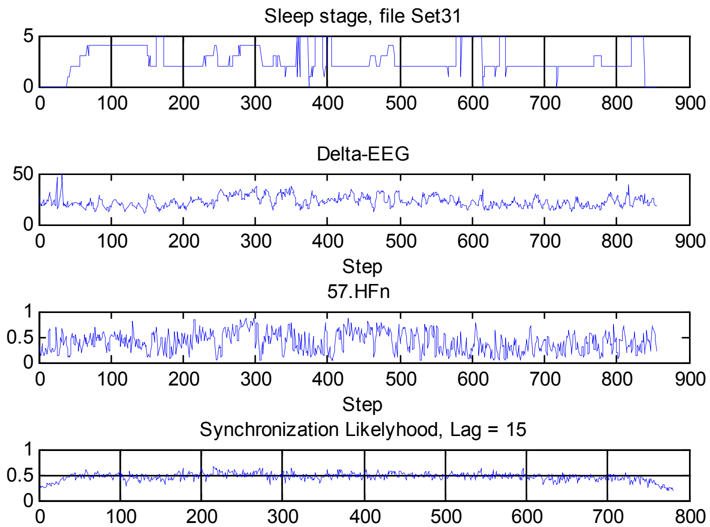
6. Shifting to the next time instant *i*+1 to obtain the time series of SL for two signals.

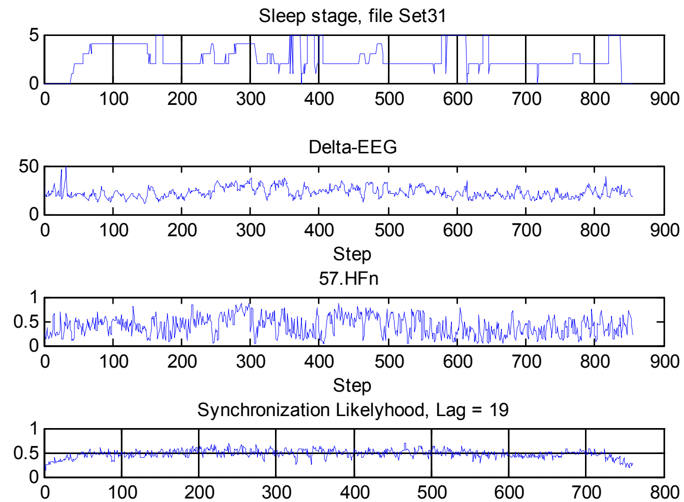
Synchronization Likelihood

Dependence on the lag value – is weak.



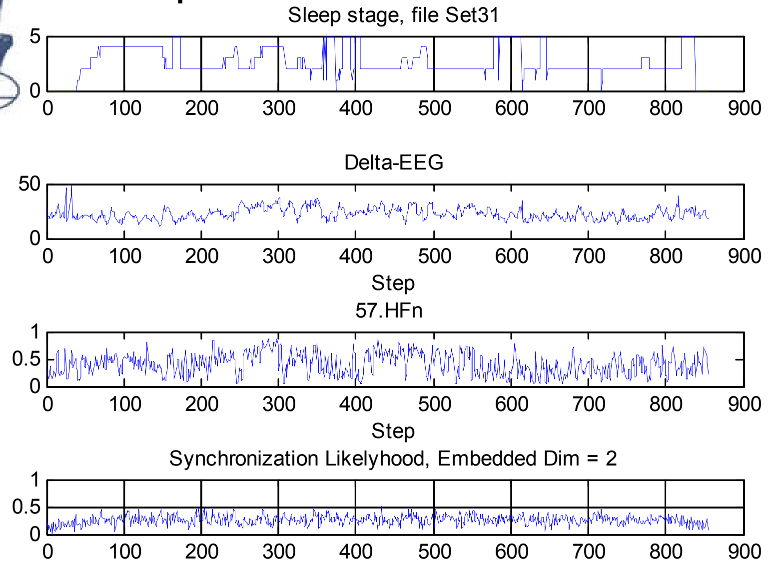


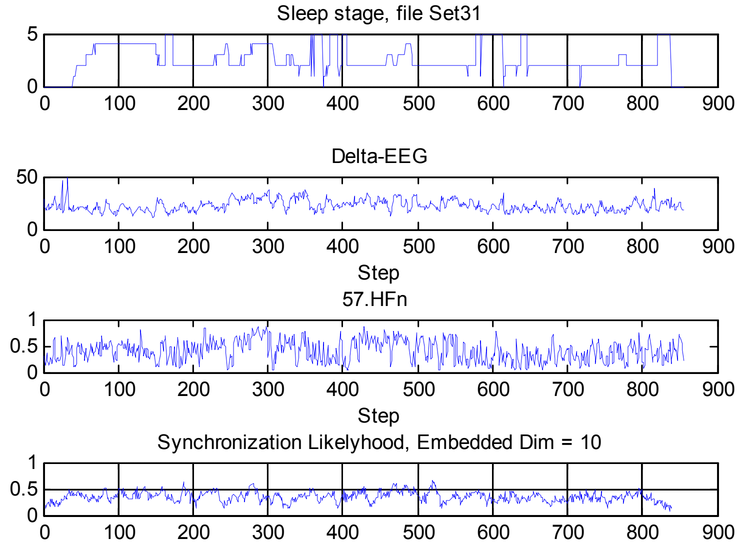


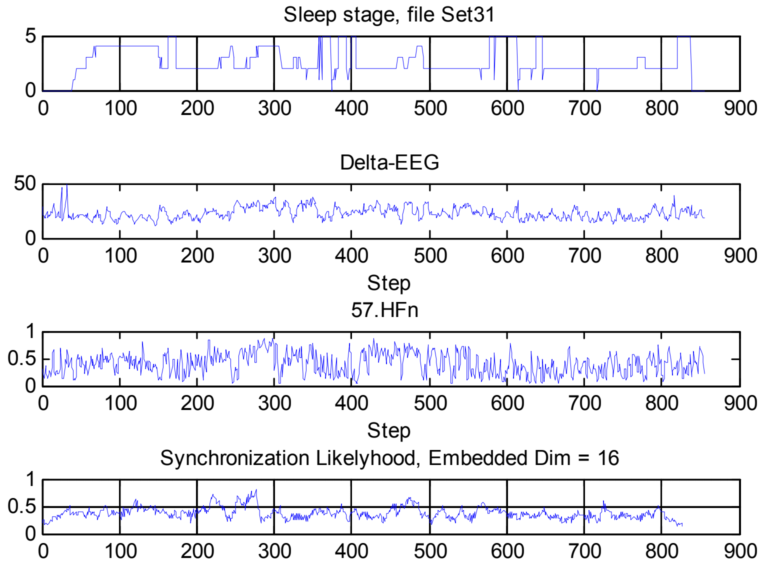


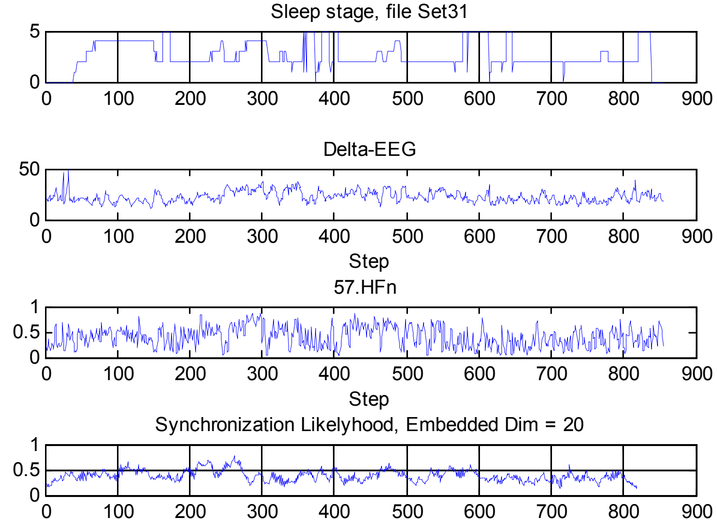
Synchronization Likelihood

Dependence on the embedded dimension – is weak.



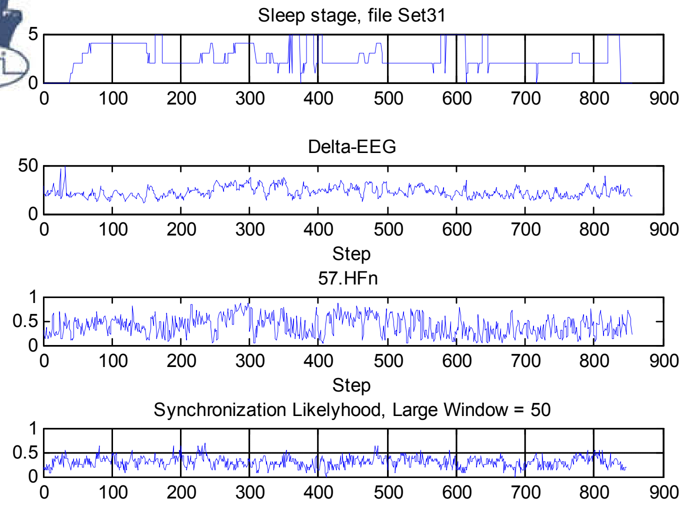


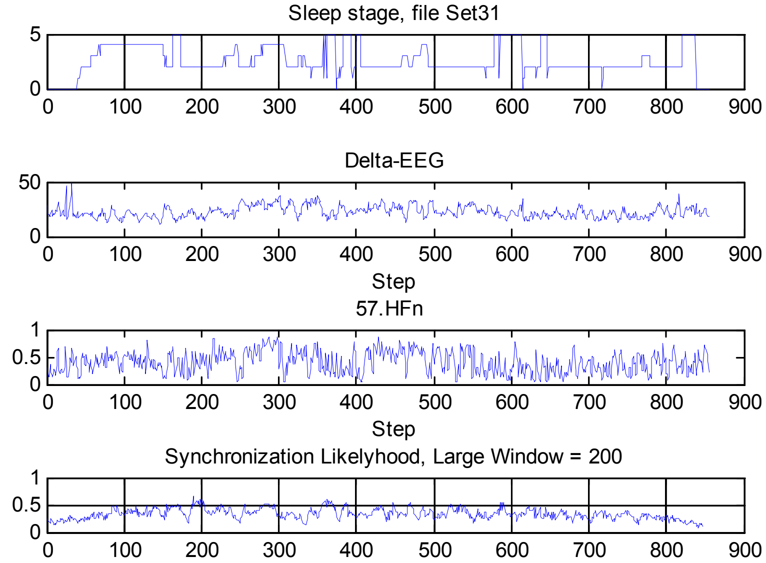


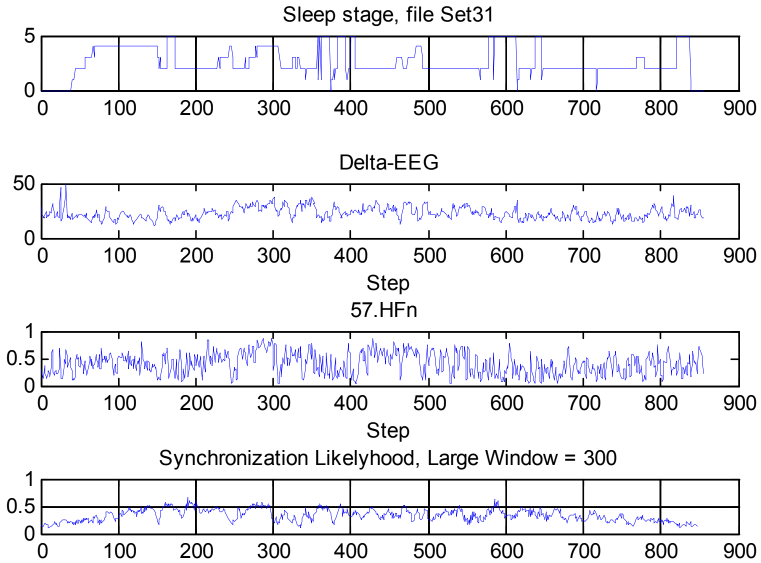


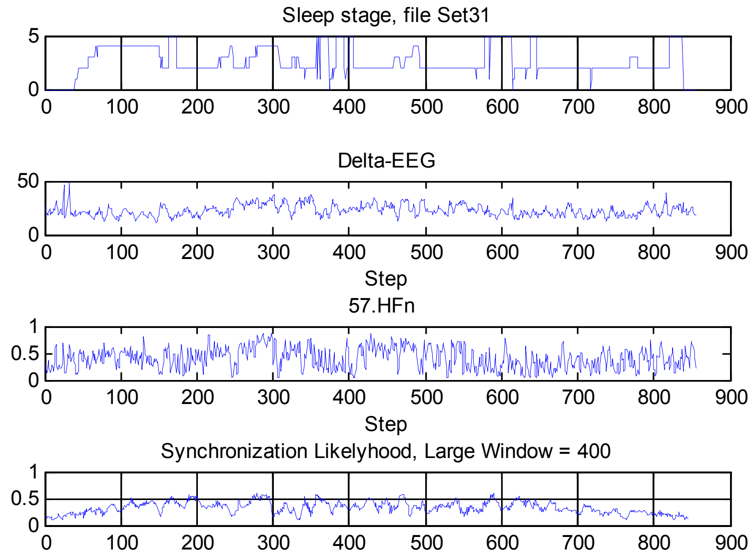
Synchronization Likelihood

Dependence on the large window size – is weak.



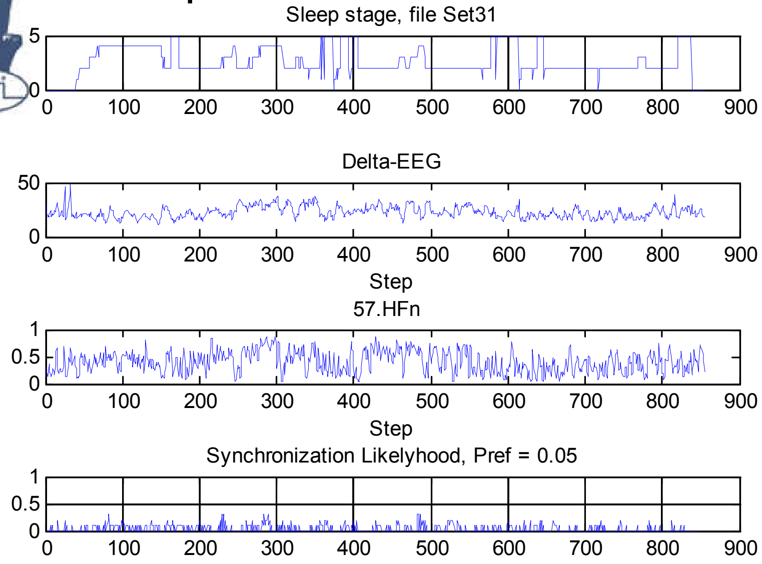


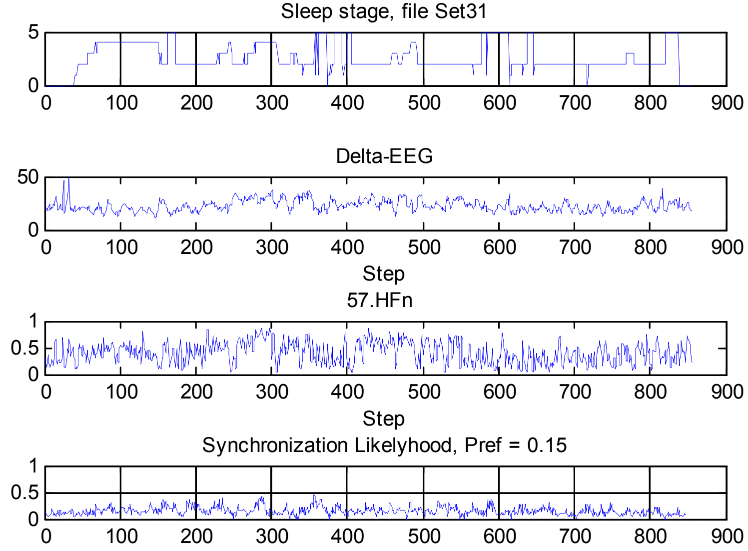


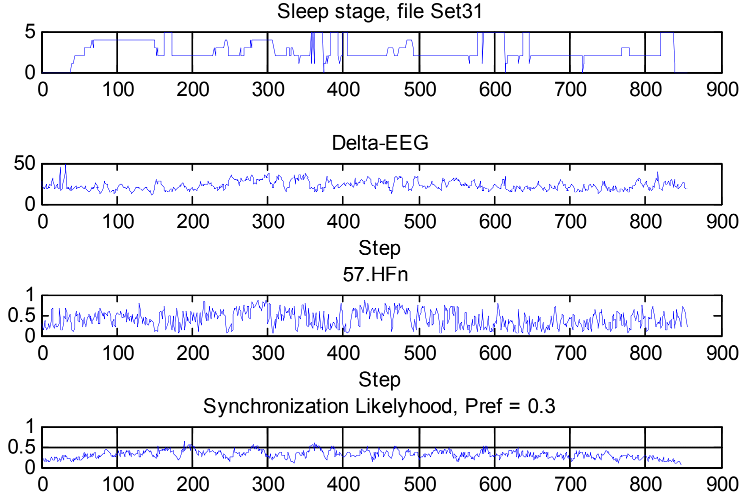


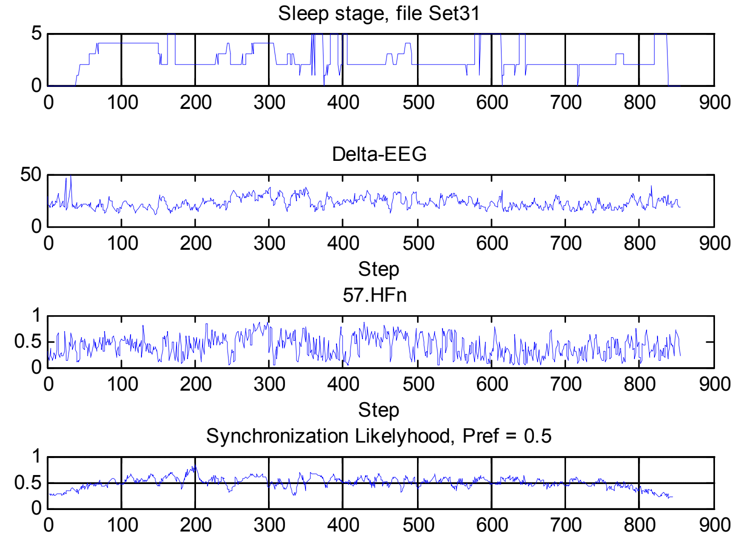
Synchronization Likelihood

Dependence on the Pref – is meaningful.





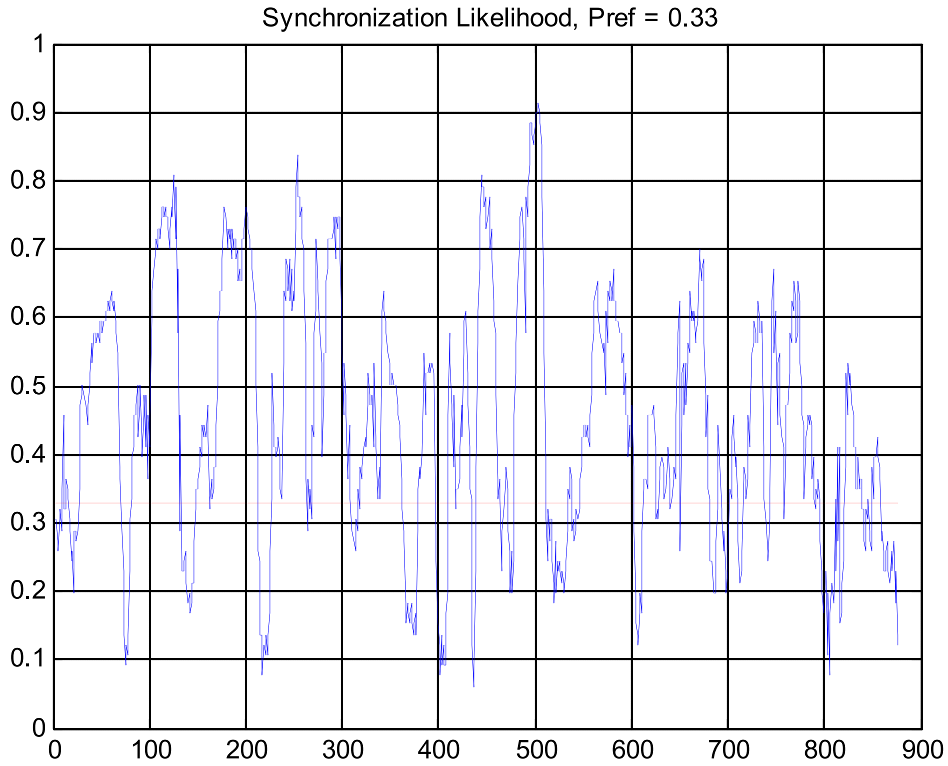




Developing the new measure for SL

The purpose – to derive the measure for selecting the HR parameters, most suitable for possible exploiting for sleep scoring.

SL takes values between 0 and 1. If SL is less than P_{ref}, the time series are still asynchronous, but if SL exceeds P_{ref}, there are enough similar patterns in the signals, thus they could be considered synchronized.



Proposed measure of parameter quality

$$Q = \frac{\text{time of SL larger than Pref}}{\text{total time asleep}}$$

Surrogate data

To demonstrate that SL is sensitive to non-liner structure of the data, the surrogate data is used.

To obtain surrogate data, in one of two signal the non-linear properties should be broken, and SL with this cleared signal should be compared with SL obtained using two raw signals.

Surrogate signal:

1. Calculate Fourier Transform of one of the signals
2. Add random numbers [0 2π] to the phases of all harmonics.
3. Perform Inverse Fourier Transform

Because only phase spectra is affected by such procedure, the power spectra is identical to the original time series. Thus the cross-spectra (correlation) and coherence properties are preserved (linear properties), while non-linear are lost.

Measure of parameter usability for sleep scoring using SL – data

Delta-EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
22. meanNN	**71,39%**	62,34%	9,05%
32. Shannon	**69,25%**	58,90%	10,35%
35. renyi2	**68,93%**	58,22%	10,71%
33. renyi025	**68,59%**	57,27%	11,32%
24. cvNN	**68,54%**	58,55%	9,99%
23. sdNN	68,53%	58,39%	10,14%
34. renyi4	68,05%	57,03%	11,02%
38. pNNl30	66,54%	59,40%	7,14%
39. pNNl50	66,30%	59,67%	6,64%
28. rmssd	66,13%	59,42%	6,71%
53. allLFtoP	65,93%	51,39%	14,54%
25. sdaNN1	65,61%	51,54%	14,06%
29. pNN50	65,47%	58,19%	7,28%
37. NNl20	65,23%	57,20%	8,03%
50. HFtoP	64,76%	52,53%	12,23%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
53. allLFtoP	65,93%	51,39%	**14,54%**
25. sdaNN1	65,61%	51,54%	**14,06%**
51. VLFtoP	61,87%	48,44%	**13,43%**
50. HFtoP	64,76%	52,53%	**12,23%**
54. UV_LFtoP	61,87%	49,92%	**11,96%**
33. renyi025	68,59%	57,27%	11,32%
34. renyi4	68,05%	57,03%	11,02%
35. renyi2	68,93%	58,22%	10,71%
55. UVLF	59,66%	49,26%	10,40%
32. Shannon	69,25%	58,90%	10,35%
41. VLF	59,66%	49,37%	10,29%
23. sdNN	68,53%	58,39%	10,14%
24. cvNN	68,54%	58,55%	9,99%
47. P	61,07%	51,14%	9,93%
36. pNNl10	63,67%	54,48%	9,19%

Measure of parameter usability for sleep scoring using SL – data

Theta-EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
22. meanNN	**69,68%**	63,19%	6,49%
32. Shannon	**66,94%**	57,27%	9,67%
35. renyi2	**66,70%**	56,35%	10,36%
24. cvNN	**66,45%**	57,44%	9,02%
23. sdNN	**66,10%**	56,73%	9,37%
33. renyi025	65,52%	57,55%	7,97%
34. renyi4	65,50%	57,23%	8,27%
39. pNNl50	65,36%	55,47%	9,89%
28. rmssd	65,08%	57,78%	7,29%
38. pNNl30	64,18%	59,75%	4,43%
29. pNN50	64,16%	55,56%	8,60%
25. sdaNN1	63,23%	51,54%	11,68%
37. NNl20	62,89%	55,33%	7,56%
53. allLFtoP	61,16%	48,59%	12,57%
50. HFtoP	60,93%	51,64%	9,28%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
53. allLFtoP	61,16%	48,59%	**12,57%**
25. sdaNN1	63,23%	51,54%	**11,68%**
51. VLFtoP	58,16%	47,41%	**10,75%**
54. UV_LFtoP	58,16%	47,52%	**10,64%**
35. renyi2	66,70%	56,35%	**10,36%**
39. pNNl50	65,36%	55,47%	9,89%
32. Shannon	66,94%	57,27%	9,67%
49. LFtoP	53,43%	43,86%	9,57%
23. sdNN	66,10%	56,73%	9,37%
55. UVLF	58,19%	48,89%	9,30%
50. HFtoP	60,93%	51,64%	9,28%
48. LFtoHF	55,90%	46,76%	9,14%
24. cvNN	66,45%	57,44%	9,02%
43. HF	60,10%	51,09%	9,01%
47. P	60,02%	51,12%	8,89%

Measure of parameter usability for sleep scoring using SL – data

Alpha-EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
22. meanNN	**70,56%**	53,87%	16,69%
23. sdNN	**69,62%**	53,47%	16,16%
24. cvNN	**69,36%**	54,37%	14,99%
35. renyi2	**68,99%**	53,95%	15,04%
32. Shannon	**68,95%**	54,68%	14,27%
34. renyi4	67,65%	52,57%	15,08%
33. renyi025	67,41%	53,91%	13,50%
28. rmssd	67,34%	54,96%	12,39%
38. pNNl30	65,85%	56,90%	8,95%
39. pNNl50	65,19%	53,77%	11,41%
25. sdaNN1	64,60%	49,90%	14,71%
29. pNN50	64,36%	54,17%	10,19%
37. NNl20	64,27%	54,42%	9,85%
47. P	64,16%	46,87%	17,29%
5. FWRENY25	63,66%	51,91%	11,74%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
55. UVLF	62,38%	44,98%	**17,39%**
47. P	64,16%	46,87%	**17,29%**
22. meanNN	70,56%	53,87%	**16,69%**
54. UV_LFtoP	62,33%	45,77%	**16,56%**
23. sdNN	69,62%	53,47%	**16,16%**
51. VLFtoP	62,33%	47,01%	15,32%
53. allLFtoP	62,58%	47,38%	15,20%
34. renyi4	67,65%	52,57%	15,08%
35. renyi2	68,99%	53,95%	15,04%
24. cvNN	69,36%	54,37%	14,99%
50. HFtoP	62,65%	47,87%	14,78%
25. sdaNN1	64,60%	49,90%	14,71%
42. LF	61,05%	46,61%	14,44%
41. VLF	62,38%	47,98%	14,40%
32. Shannon	68,95%	54,68%	14,27%

Measure of parameter usability for sleep scoring using SL – data

Beta-EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
24. cvNN	**75,32%**	50,89%	24,43%
23. sdNN	**74,52%**	52,17%	22,35%
32. Shannon	**73,01%**	52,41%	20,61%
35. renyi2	**72,70%**	52,86%	19,83%
22. meanNN	**72,54%**	53,83%	18,71%
34. renyi4	72,31%	48,95%	23,36%
33. renyi025	71,93%	50,96%	20,98%
25. sdaNN1	71,82%	46,79%	25,03%
47. P	69,48%	45,27%	24,21%
28. rmssd	68,46%	50,71%	17,75%
41. VLF	68,23%	44,64%	23,59%
55. UVLF	68,23%	44,18%	24,05%
53. allLFtoP	67,79%	45,31%	22,48%
51. VLFtoP	67,58%	44,73%	22,85%
54. UV_LFtoP	67,58%	44,79%	22,79%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
25. sdaNN1	71,82%	46,79%	**25,03%**
24. cvNN	75,32%	50,89%	**24,43%**
47. P	69,48%	45,27%	**24,21%**
55. UVLF	68,23%	44,18%	**24,05%**
41. VLF	68,23%	44,64%	**23,59%**
34. renyi4	72,31%	48,95%	**23,36%**
51. VLFtoP	67,58%	44,73%	22,85%
54. UV_LFtoP	67,58%	44,79%	22,79%
53. allLFtoP	67,79%	45,31%	22,48%
23. sdNN	74,52%	52,17%	22,35%
33. renyi025	71,93%	50,96%	20,98%
32. Shannon	73,01%	52,41%	20,61%
35. renyi2	72,70%	52,86%	19,83%
22. meanNN	72,54%	53,83%	18,71%
42. LF	62,51%	43,83%	18,68%

Measure of parameter usability for sleep scoring using SL – data

Beta/Delta EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
24. cvNN	**74,84%**	56,20%	18,64%
23. sdNN	**74,27%**	53,82%	20,46%
25. sdaNN1	**74,26%**	50,55%	23,71%
35. renyi2	**73,13%**	55,75%	17,38%
32. Shannon	**73,06%**	54,33%	18,73%
53. allLFtoP	72,54%	47,95%	24,59%
34. renyi4	72,49%	54,58%	17,91%
33. renyi025	72,41%	54,24%	18,18%
22. meanNN	71,63%	57,51%	14,12%
51. VLFtoP	70,06%	46,70%	23,36%
54. UV_LFtoP	70,06%	44,98%	25,09%
50. HFtoP	68,74%	47,27%	21,47%
41. VLF	68,71%	49,47%	19,24%
55. UVLF	68,71%	48,52%	20,19%
47. P	67,20%	46,17%	21,02%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
54. UV_LFtoP	70,06%	44,98%	**25,09%**
53. allLFtoP	72,54%	47,95%	**24,59%**
25. sdaNN1	74,26%	50,55%	**23,71%**
51. VLFtoP	70,06%	46,70%	**23,36%**
50. HFtoP	68,74%	47,27%	**21,47%**
47. P	67,20%	46,17%	21,02%
23. sdNN	74,27%	53,82%	20,46%
55. UVLF	68,71%	48,52%	20,19%
41. VLF	68,71%	49,47%	19,24%
32. Shannon	73,06%	54,33%	18,73%
24. cvNN	74,84%	56,20%	18,64%
33. renyi025	72,41%	54,24%	18,18%
34. renyi4	72,49%	54,58%	17,91%
35. renyi2	73,13%	55,75%	17,38%
49. LFtoP	60,10%	44,58%	15,52%

Measure of parameter usability for sleep scoring using SL – data

Beta/Theta EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
24. cvNN	**74,00%**	55,69%	18,31%
23. sdNN	**73,29%**	52,62%	20,67%
25. sdaNN1	**72,73%**	49,50%	23,23%
32. Shannon	**71,80%**	53,57%	18,23%
33. renyi025	**71,54%**	52,65%	18,89%
35. renyi2	71,36%	54,57%	16,78%
34. renyi4	70,45%	53,52%	16,93%
22. meanNN	69,89%	56,44%	13,45%
53. allLFtoP	68,35%	49,14%	19,22%
28. rmssd	67,57%	53,66%	13,91%
41. VLF	66,78%	46,10%	20,68%
55. UVLF	66,78%	45,05%	21,73%
47. P	66,33%	48,52%	17,81%
51. VLFtoP	66,23%	45,36%	20,87%
54. UV_LFtoP	66,23%	45,31%	20,92%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
25. sdaNN1	72,73%	49,50%	**23,23%**
55. UVLF	66,78%	45,05%	**21,73%**
54. UV_LFtoP	66,23%	45,31%	**20,92%**
51. VLFtoP	66,23%	45,36%	**20,87%**
41. VLF	66,78%	46,10%	**20,68%**
23. sdNN	73,29%	52,62%	20,67%
53. allLFtoP	68,35%	49,14%	19,22%
33. renyi025	71,54%	52,65%	18,89%
24. cvNN	74,00%	55,69%	18,31%
32. Shannon	71,80%	53,57%	18,23%
47. P	66,33%	48,52%	17,81%
34. renyi4	70,45%	53,52%	16,93%
35. renyi2	71,36%	54,57%	16,78%
50. HFtoP	62,76%	46,95%	15,81%
49. LFtoP	59,74%	44,12%	15,62%

Measure of parameter usability for sleep scoring using SL – data

Beta/Alpha EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
22. meanNN	**69,10%**	56,31%	12,78%
24. cvNN	**67,80%**	52,97%	14,83%
23. sdNN	**67,22%**	52,12%	15,11%
32. Shannon	**66,56%**	51,88%	14,68%
33. renyi025	**66,29%**	53,18%	13,11%
35. renyi2	65,34%	51,61%	13,73%
34. renyi4	64,68%	53,42%	11,26%
25. sdaNN1	64,38%	50,13%	14,25%
28. rmssd	62,70%	53,46%	9,24%
53. allLFtoP	62,43%	46,60%	15,83%
39. pNNl50	61,07%	53,41%	7,66%
47. P	60,95%	47,80%	13,15%
29. pNN50	60,59%	52,36%	8,23%
38. pNNl30	60,35%	55,29%	5,06%
51. VLFtoP	60,33%	46,59%	13,74%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
54. UV_LFtoP	60,33%	43,39%	**16,94%**
41. VLF	60,33%	43,39%	**16,93%**
53. allLFtoP	62,43%	46,60%	**15,83%**
23. sdNN	67,22%	52,12%	**15,11%**
24. cvNN	67,80%	52,97%	**14,83%**
32. Shannon	66,56%	51,88%	14,68%
25. sdaNN1	64,38%	50,13%	14,25%
55. UVLF	60,33%	46,15%	14,18%
51. VLFtoP	60,33%	46,59%	13,74%
35. renyi2	65,34%	51,61%	13,73%
47. P	60,95%	47,80%	13,15%
33. renyi025	66,29%	53,18%	13,11%
22. meanNN	69,10%	56,31%	12,78%
50. HFtoP	58,96%	47,20%	11,76%
34. renyi4	64,68%	53,42%	11,26%

Measure of parameter usability for sleep scoring using SL – data

Alpha/Delta EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
24. cvNN	**72,63%**	54,32%	18,31%
23. sdNN	**72,36%**	53,13%	19,23%
32. Shannon	**71,80%**	52,80%	19,00%
33. renyi025	**71,78%**	53,59%	18,19%
35. renyi2	**71,26%**	53,75%	17,51%
22. meanNN	71,10%	53,42%	17,69%
34. renyi4	70,06%	51,46%	18,60%
25. sdaNN1	69,54%	50,42%	19,13%
41. VLF	67,29%	45,45%	21,84%
55. UVLF	67,29%	47,56%	19,73%
28. rmssd	66,98%	52,63%	14,35%
53. allLFtoP	66,94%	49,77%	17,17%
47. P	66,56%	47,82%	18,74%
51. VLFtoP	65,19%	46,67%	18,53%
54. UV_LFtoP	65,19%	46,60%	18,59%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
41. VLF	67,29%	45,45%	**21,84%**
55. UVLF	67,29%	47,56%	**19,73%**
23. sdNN	72,36%	53,13%	**19,23%**
25. sdaNN1	69,54%	50,42%	**19,13%**
32. Shannon	71,80%	52,80%	**19,00%**
47. P	66,56%	47,82%	18,74%
34. renyi4	70,06%	51,46%	18,60%
54. UV_LFtoP	65,19%	46,60%	18,59%
51. VLFtoP	65,19%	46,67%	18,53%
24. cvNN	72,63%	54,32%	18,31%
33. renyi025	71,78%	53,59%	18,19%
22. meanNN	71,10%	53,42%	17,69%
35. renyi2	71,26%	53,75%	17,51%
53. allLFtoP	66,94%	49,77%	17,17%
50. HFtoP	64,67%	48,44%	16,23%

Measure of parameter usability for sleep scoring using SL – data

Alpha/Theta EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
22. meanNN	**70,72%**	56,42%	14,30%
24. cvNN	**69,40%**	52,81%	16,59%
23. sdNN	**69,22%**	51,51%	17,71%
32. Shannon	**68,06%**	54,07%	13,99%
33. renyi025	**67,50%**	52,75%	14,75%
35. renyi2	67,46%	53,45%	14,01%
34. renyi4	66,96%	55,06%	11,90%
28. rmssd	66,65%	54,68%	11,97%
25. sdaNN1	65,75%	48,37%	17,38%
47. P	65,11%	49,87%	15,24%
37. NNl20	64,71%	52,78%	11,93%
38. pNNl30	63,88%	55,03%	8,85%
39. pNNl50	62,97%	54,75%	8,22%
45. YF	62,57%	50,38%	12,19%
46. ZF	62,56%	49,30%	13,26%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
23. sdNN	69,22%	51,51%	**17,71%**
55. UVLF	62,56%	44,89%	**17,67%**
25. sdaNN1	65,75%	48,37%	**17,38%**
41. VLF	62,56%	45,46%	**17,09%**
24. cvNN	69,40%	52,81%	**16,59%**
53. allLFtoP	62,39%	46,81%	15,58%
51. VLFtoP	60,11%	44,67%	15,44%
47. P	65,11%	49,87%	15,24%
33. renyi025	67,50%	52,75%	14,75%
48. LFtoHF	58,95%	44,22%	14,72%
43. HF	62,42%	47,85%	14,57%
22. meanNN	70,72%	56,42%	14,30%
35. renyi2	67,46%	53,45%	14,01%
32. Shannon	68,06%	54,07%	13,99%
54. UV_LFtoP	60,11%	46,50%	13,61%

Measure of parameter usability for sleep scoring using SL – data

Theta/Delta EEG **vs** *all HRV parameters*

Top 15 with largest quality

Parameter name	Real signal	Surrogate signal	delta
22. meanNN	**70,44%**	56,87%	13,57%
35. renyi2	**70,10%**	54,23%	15,88%
32. Shannon	**69,79%**	54,03%	15,76%
24. cvNN	**69,40%**	53,75%	15,65%
23. sdNN	**69,33%**	53,57%	15,76%
34. renyi4	69,23%	55,49%	13,75%
33. renyi025	68,80%	54,93%	13,86%
38. pNNl30	68,48%	55,79%	12,69%
53. allLFtoP	67,94%	51,57%	16,37%
39. pNNl50	67,03%	55,16%	11,87%
28. rmssd	66,80%	55,31%	11,50%
25. sdaNN1	66,30%	51,14%	15,16%
37. NNl20	66,22%	55,33%	10,89%
29. pNN50	65,59%	56,41%	9,18%
50. HFtoP	64,97%	49,82%	15,14%

Top 15 with largest difference

Parameter name	Real signal	Surrogate signal	delta
51. VLFtoP	63,76%	45,86%	**17,90%**
55. UVLF	62,84%	45,22%	**17,61%**
53. allLFtoP	67,94%	51,57%	**16,37%**
35. renyi2	70,10%	54,23%	**15,88%**
23. sdNN	69,33%	53,57%	**15,76%**
41. VLF	62,84%	47,07%	15,76%
32. Shannon	69,79%	54,03%	15,76%
24. cvNN	69,40%	53,75%	15,65%
54. UV_LFtoP	63,76%	48,27%	15,49%
25. sdaNN1	66,30%	51,14%	15,16%
50. HFtoP	64,97%	49,82%	15,14%
47. P	63,28%	48,51%	14,78%
33. renyi025	68,80%	54,93%	13,86%
34. renyi4	69,23%	55,49%	13,75%
22. meanNN	70,44%	56,87%	13,57%

Measure of parameter usability for sleep scoring using SL – results-1

Parameter name	Number of occurrences in top-5 with high Q
32. Shannon	10
23. sdNN	10
24. cvNN	9
22. meanNN	7
33. renyi025	6
25. sdaNN1	6
35. renyi2	2

In Top-5 there are 3 parameters of chaoticity (Shannon and Renyi entropies) and 4 statistical parameters. Entropy parameters occurs 18 times, while statistical – 32 times.

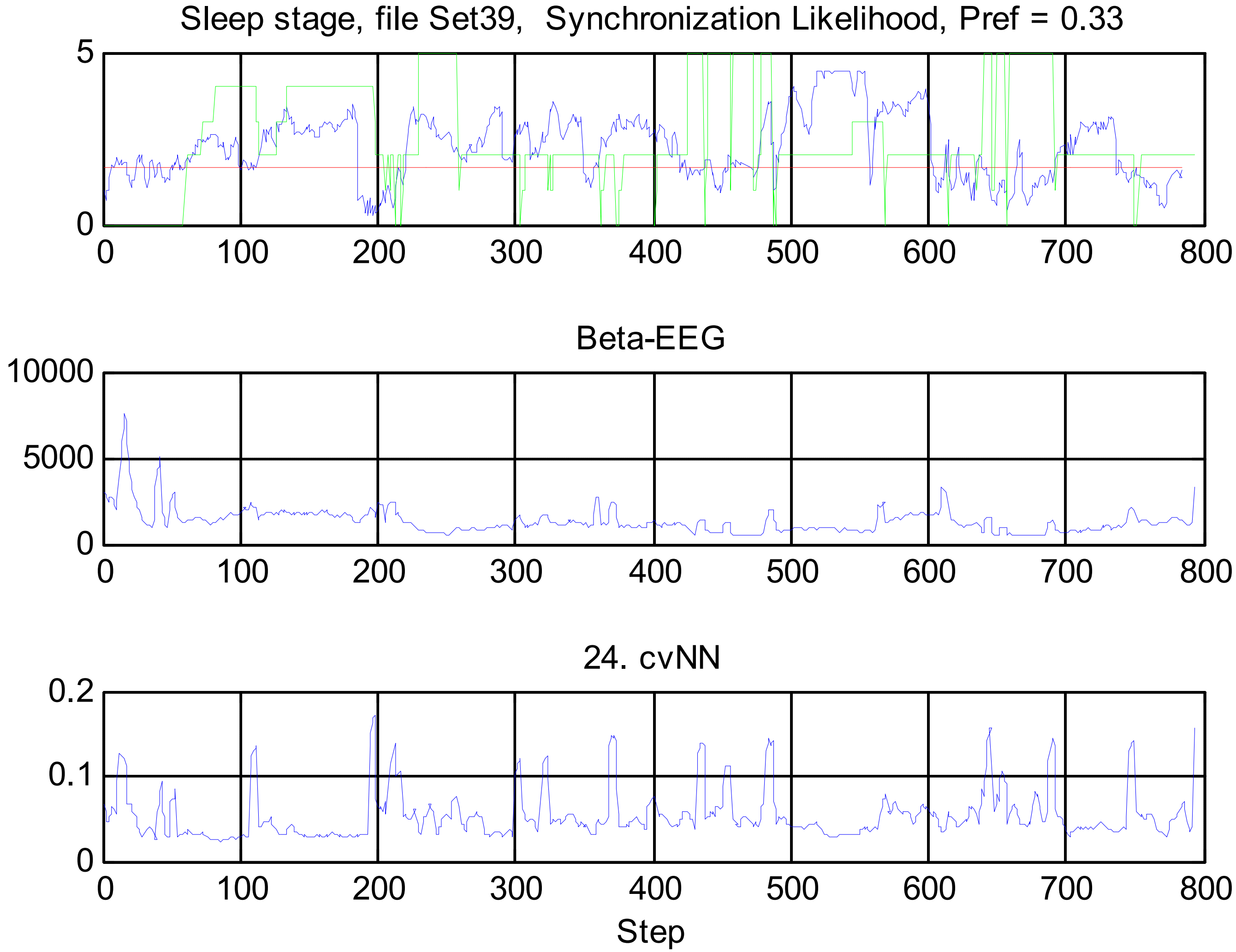
	EEG-parameter	HR parameter with highest Q	%
4	*Beta-EEG*	**24. cvNN**	75,32%
5	*Beta/Delta EEG*	24. cvNN	74,84%
6	*Beta/Theta EEG*	24. cvNN	74,00%
8	*Alpha/Delta EEG*	24. cvNN	72,63%
1	*Delta-EEG*	22. meanNN	71,39%
9	*Alpha/Theta EEG*	22. meanNN	70,72%
3	*Alpha-EEG*	**22. meanNN**	70,56%
10	*Theta/Delta EEG*	22. meanNN	70,44%
2	*Theta-EEG*	22. meanNN	69,68%
7	*Beta/Alpha EEG*	22. meanNN	69,10%

In Top-1 parameters with high Q there are only statistical parameters. Among ten EEG characteristics, six are maximally synchronized with **meanNN** and four with **cvNN**.

Highest synchronicity showed **cvNN** with **Beta-EEG**.

Measure of parameter usability for sleep scoring using SL – results-2

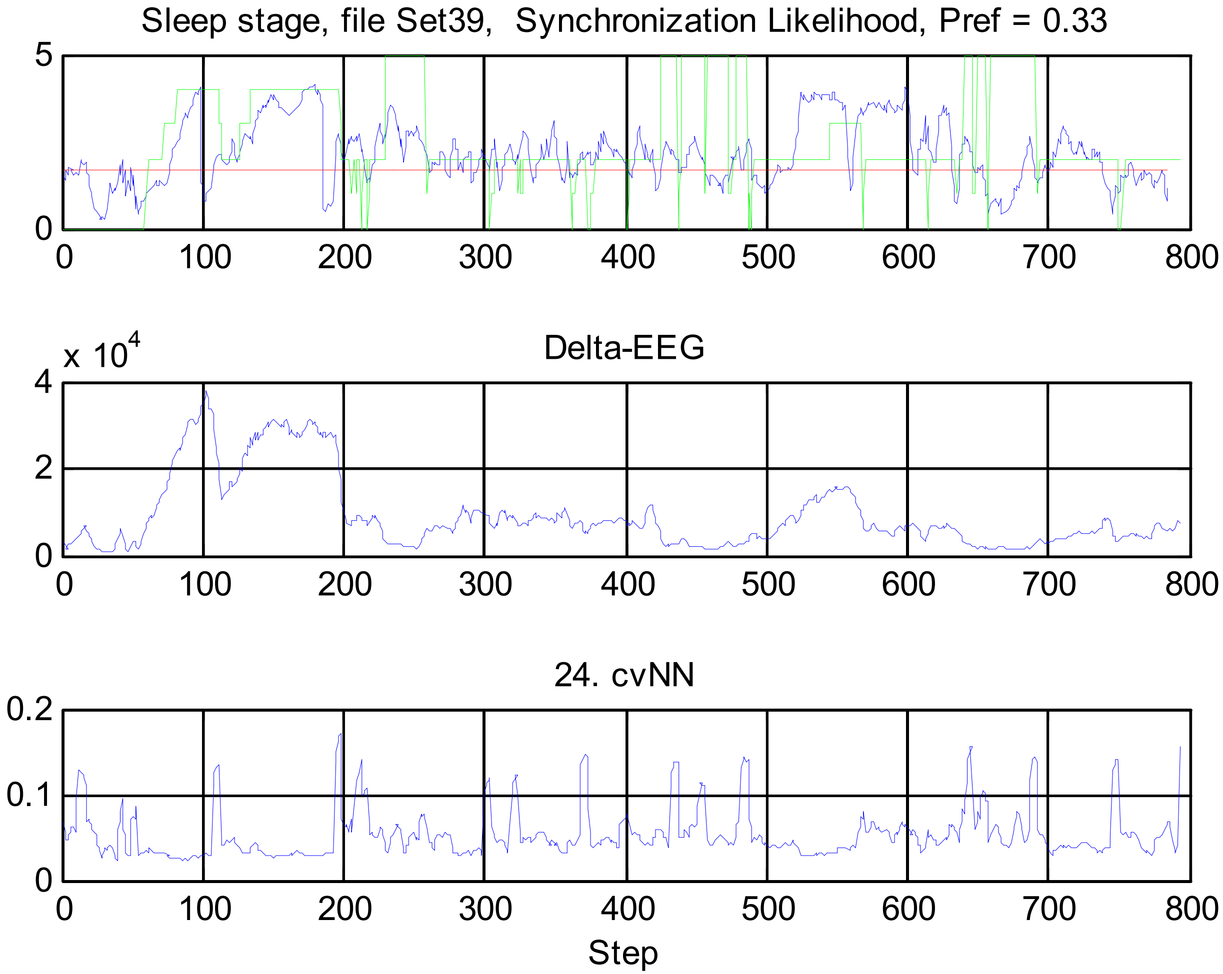
Synchronization Likelihood between Beta-EEG and cvNN



There are evident synchronous changes in two signals, but its hard to tell if these changes reflect the sleep stages.

Measure of parameter usability for sleep scoring using SL – results-3

Synchronization Likelihood between Delta-EEG and cvNN



There are evident synchronous changes in two signals, but its hard to tell if these changes reflect the sleep stages.

Measure of parameter usability for sleep scoring using SL – results-4

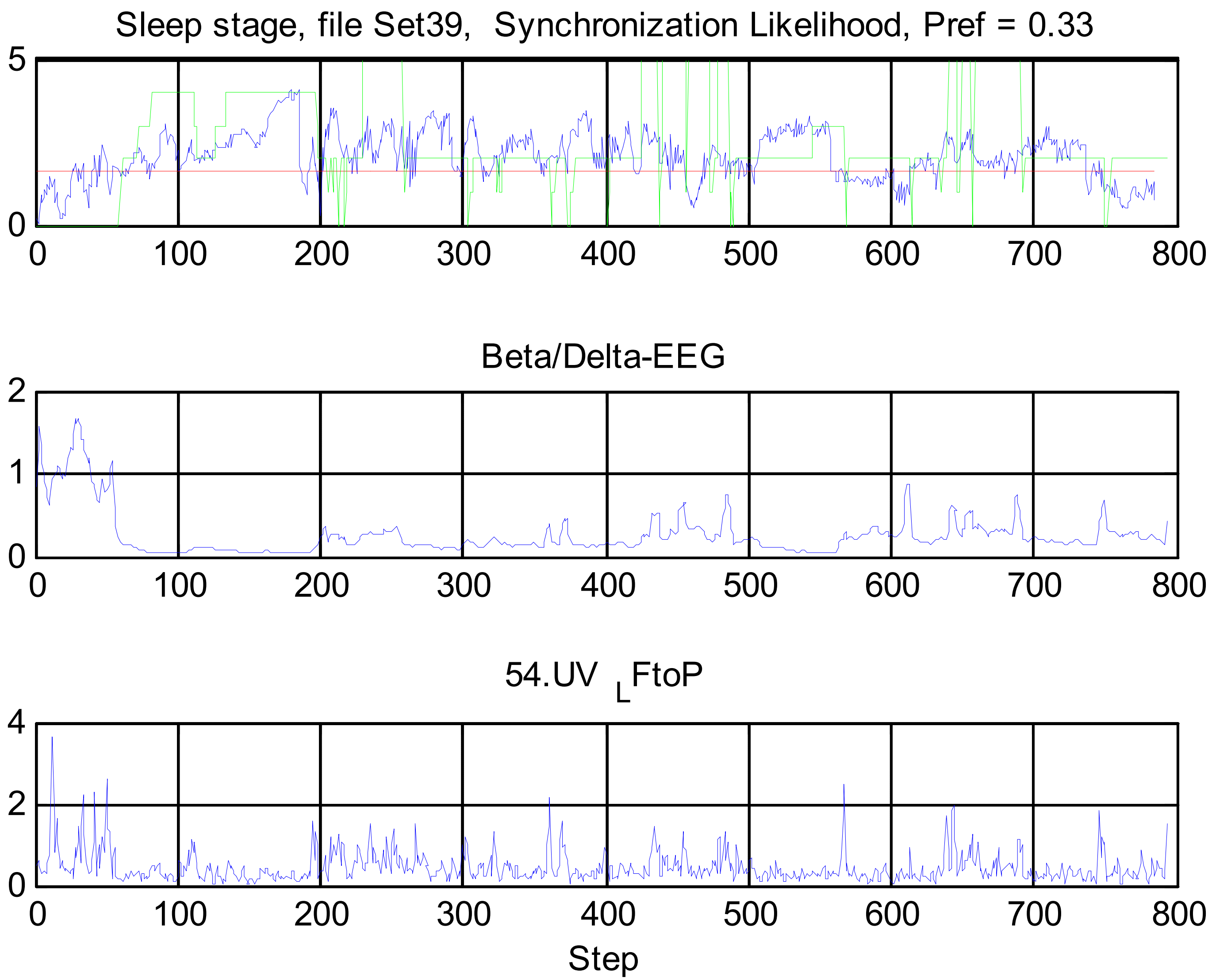
	EEG-parameter	Parameter with highest Q and largest Delta	delta
5	*Beta/Delta EEG*	54. UV_LFtoP	25,09%
4	*Beta-EEG*	25. sdaNN1	25,03%
6	*Beta/Theta EEG*	**25. sdaNN1**	23,23%
8	*Alpha/Delta EEG*	41. VLF	21,84%
10	*Theta/Delta EEG*	51. VLFtoP	17,90%
9	*Alpha/Theta EEG*	**23. sdNN**	17,71%
3	*Alpha-EEG*	55. UVLF	17,39%
7	*Beta/Alpha EEG*	54. UV_LFtoP	16,94%
1	*Delta-EEG*	53. allLFtoP	14,54%
2	*Theta-EEG*	53. allLFtoP	12,57%

In Top-1 parameters for which the difference between SL for real and surrogated data is largest, there are only spectral parameters and statistical parameters.

The explanation could be that other measures are not sensitive to the nonlinearities inherent to these time series.

Measure of parameter usability for sleep scoring using SL – results-5

Synchronization Likelihood between *Beta/Delta* -EEG and UV_LFtoP



SL - Conclusions

1. From the point of view of synchronization likelihood, **meanNN** and **cvNN** are most likely to change together with the change in electrical brain activity. It should be proven for other set of SL calculating parameters (such as Pref, w1, w2, m, l), although there seems to be weak dependence of SL on them.

2. Nevertheless the pair cvNN+BetaEEG has the highest Q, we have to estimate if there is a direct connection between BetaEEG and sleep stages. Only in this case we can further use the cvNN as a sleep scoring parameter.

3. We can conclude that there are some HRV parameters that are changing in substantial synchrony with brain electrical activity during sleep. SL can be regarded as adequate measure of such synchrony and as the tool for selecting such parameters.

SL - Open problems and Future work-1

1. Starting from the SL as a measure of existence of synchronicity of the signals from brain and heart we have to define the type of coupling between two systems. Predominant direction of the coupling is of great importance not for sleep stage scoring but for sleep study in general.

2. How to measure SL with SLEEP STAGES directly. The somnogram is piecewise constant signal, thus it is hardly suitable for direct SL calculations. New measure is under developing now.

3. We have to try other then Euclidean distance measures for the closeness of embedded vectors, maybe we will achieve better results.

4. We have to check, during which sleep stages SL is maximum, or Q is highest, and probably construct adaptive measure. The limited time resolution of SL measure will be a problem as well.

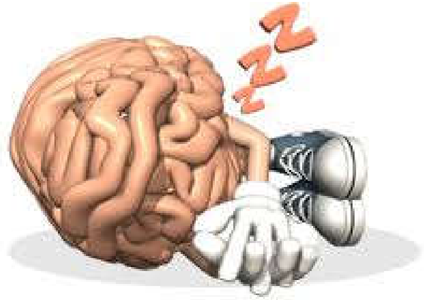
5. We have to check, will the proposed quality parameter be still adequate if we decrease the Pref.

SL - Open problems and Future work-2

1. Comparing the results for surrogate and real signals data we can conclude that the difference is not so large. This could mean that the non-linear dependence between two signals is not too prominent and during the night when human body sleeps, mainly linear mechanisms of coupling take place between two systems.

2. HF parameter has a low quality in all cases. From the other hand, in most of literature the authors emphasize on usability of HF, HFn, LF/HF for sleep stage scoring. We have to evaluate more in details these parameters with SL before derive any crucial conclusions about their applicability.

Mutual Information



Information-theoretical approaches to coupling estimation

1. Predictability approach.

Predictability is interpreted as code length, required to encode the time series by predictive coding. The more predictable time series is, the smaller number of bits is required to describe it using predictive coding. The measure could be derived using the codelengths for predicting one signal by knowing another.

2. Permutation entropy.

The problem of coupling direction in general synchronization:

1. Mutual predictability of amplitudes
2. Mutual nearest neighbors in reconstructed state spaces
3. Informational-theoretic approach
    - Interrelation of inst. phases

Mutual Information-1

This measure indicates the amount of information about random variable X we obtain by knowing Y and vise versa.

Main advantages:

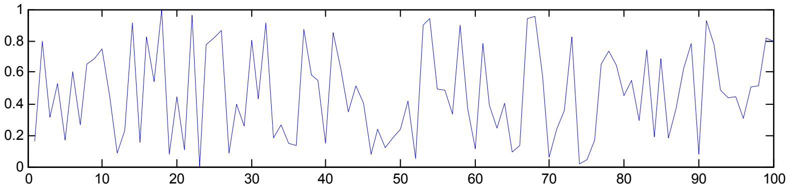
– directionality index can be defined which sows the direction of information flow and driver-response interactions between two systems; it varies between -1 and 1

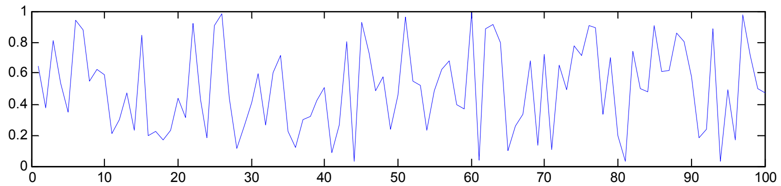
The permutation conditional mutual information (PCMI) is the method which is based on probability distribution of permutation and conditional mutual information.

Mutual Information-2

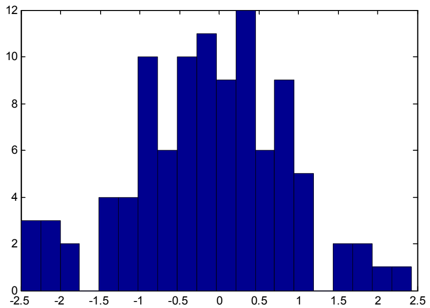
Theoretical Background

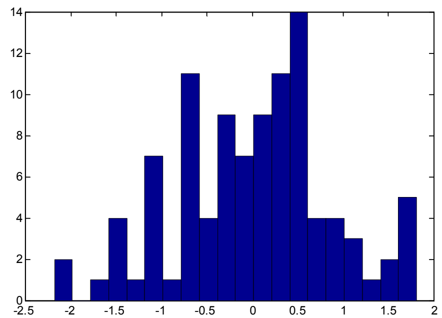
Let X=x(t) and Y=y(t) are two signal recorded from two systems



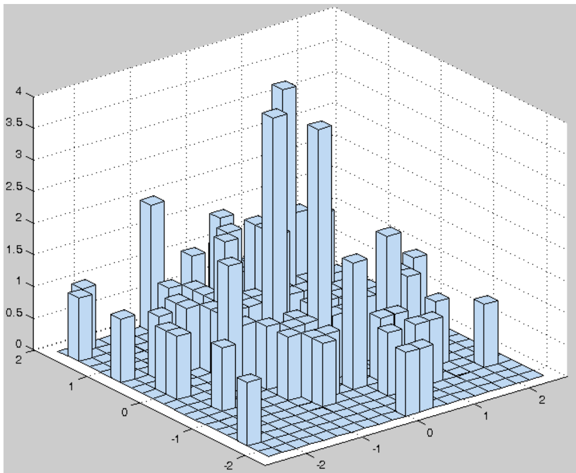


p(x) and p(y) – marginal probability distribution functions;





p(x,y) – joint pdf



Mutual Information-3

Theoretical Background

The Shannon entropy of X and Y is defined as

$$H(X) = -\sum_{x \in X} p(x) \log p(x) \qquad H(Y) = -\sum_{y \in Y} p(y) \log p(y)$$

The joint entropy is defined as

$$H(X,Y) = -\sum_{x \in X} \sum_{y \in Y} p(x,y) \log p(x,y)$$

Conditional entropy H(X|Y) of variable X given the values of Y is defined

$$H(X|Y) = -\sum_{x \in X} \sum_{y \in Y} p(x,y) \log p(x|y)$$

Common information, which is contained in both X and Y can be estimated as mutual information:

$$I(X;Y) = H(X) + H(Y) - H(X,Y)$$

Mutual Information-4

Theoretical Background этот слайд не нужен, т.к. Мы не искомльзуем PCMI

The Conditional Mutual Information (CMI) between two series X and Y can be estimated as

$$I^{\delta}_{X\to Y} = I(X;Y_{\delta}|Y) = H(X|Y) + H(Y_{\delta}|Y) - H(X,Y_{\delta}|Y)$$

$$I^{\delta}_{Y\to X} = I(Y;X_{\delta}|X) = H(Y|X) + H(X_{\delta}|X) - H(Y,X_{\delta}|X)$$

Here

$$X_{\delta}: x_{t+\delta} = x_t \;\; (Y_{\delta}: y_{t+\delta} = y_t)$$

are observables derived from the signals X and Y δ steps in future

The amount of information that is transferred from the process X to process Y (and from Y to X) at some later points in time can be defined as

$$I_{X\to Y} = \frac{1}{N}\sum_{\delta=1}^{N} I^{\delta}_{X\to Y} \qquad\qquad I_{Y\to X} = \frac{1}{N}\sum_{\delta=1}^{N} I^{\delta}_{Y\to X}$$

N – is maximal later points

Mutual Information-5

Theoretical Background

The directionality index based on the conditional mutual information:

$$D_{XY} = \left(\frac{I_{X \to Y} - I_{Y \to X}}{I_{X \to Y} + I_{Y \to X}} \right)$$

$0 < D_{XY} < 1$ – process X drives process Y in the statistical sense
$-1 < D_{XY} < 0$ – the system Y drives system X
$D_{XY} = 0$ – interactions between systems X and Y are nearly symmetrical

The problems are:

1. Estimate marginal probability functions of X and Y and their joint probability (often by histogram method). The bin number should be determined, thus the assumptions about the pdf shape should be made.
2. Selection of steps δ to be made in future of the processes. This parameter depends on the phase differences between two processes and can be made by the trial-and-error method.

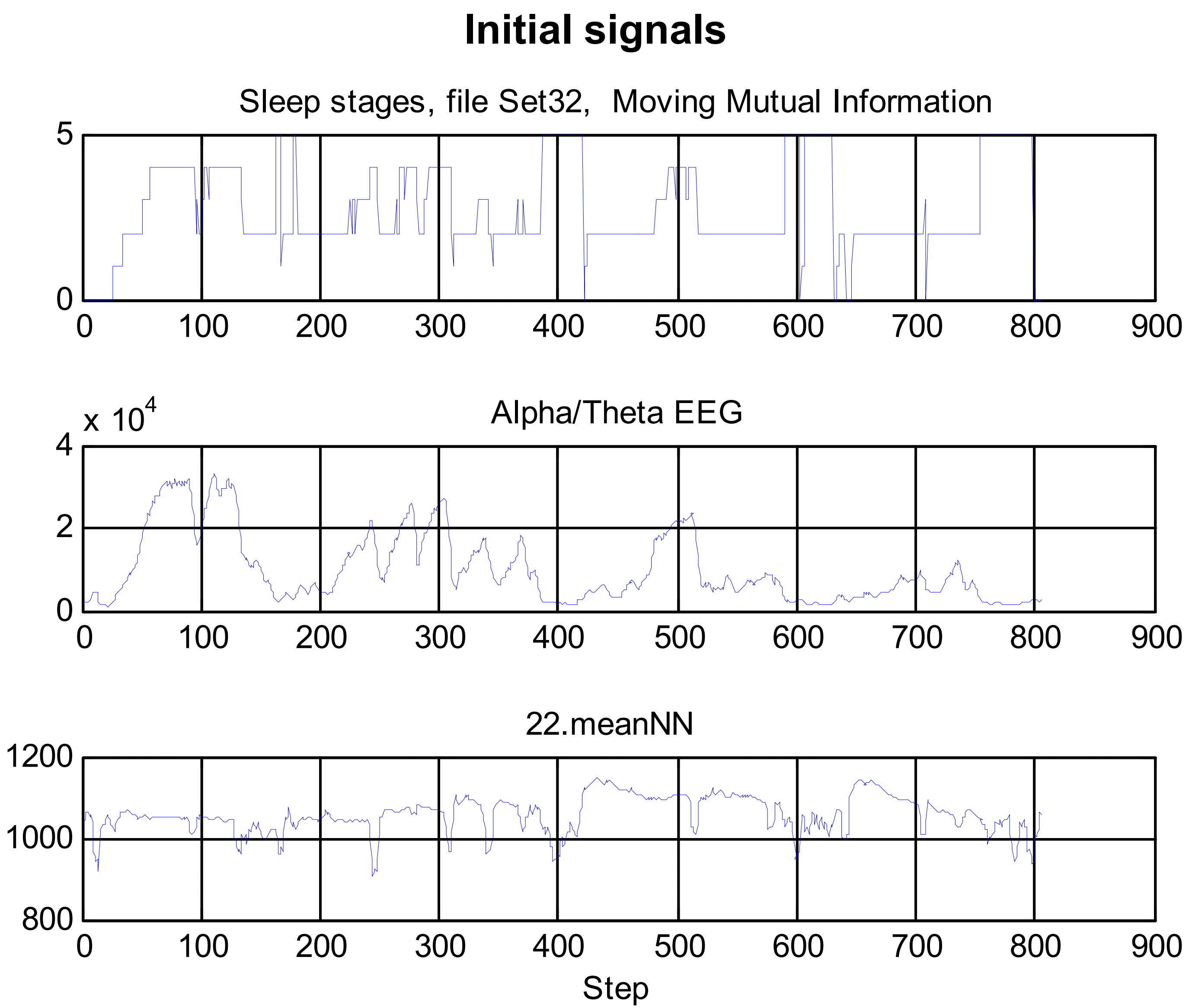
Testing MI for different settings-1

The purpose – to test MI measure for different time window lengths and for different bin numbers in histogram.

1. The pairs of signals were composed.
2. The proposed ***Moving Mutual Information*** is calculated for all EEG signals and the most valuable HRV-parameters, found in previous experiments: meanNN, sdNN, Shannon entropy. As EEG parameter Alpha/Theta ratio is selected.
3. Time windows durations were selected from 5 min to 2 hours for fixed bin number.
4. Bin numbers were selected from 10 to 120 for fixed time window.

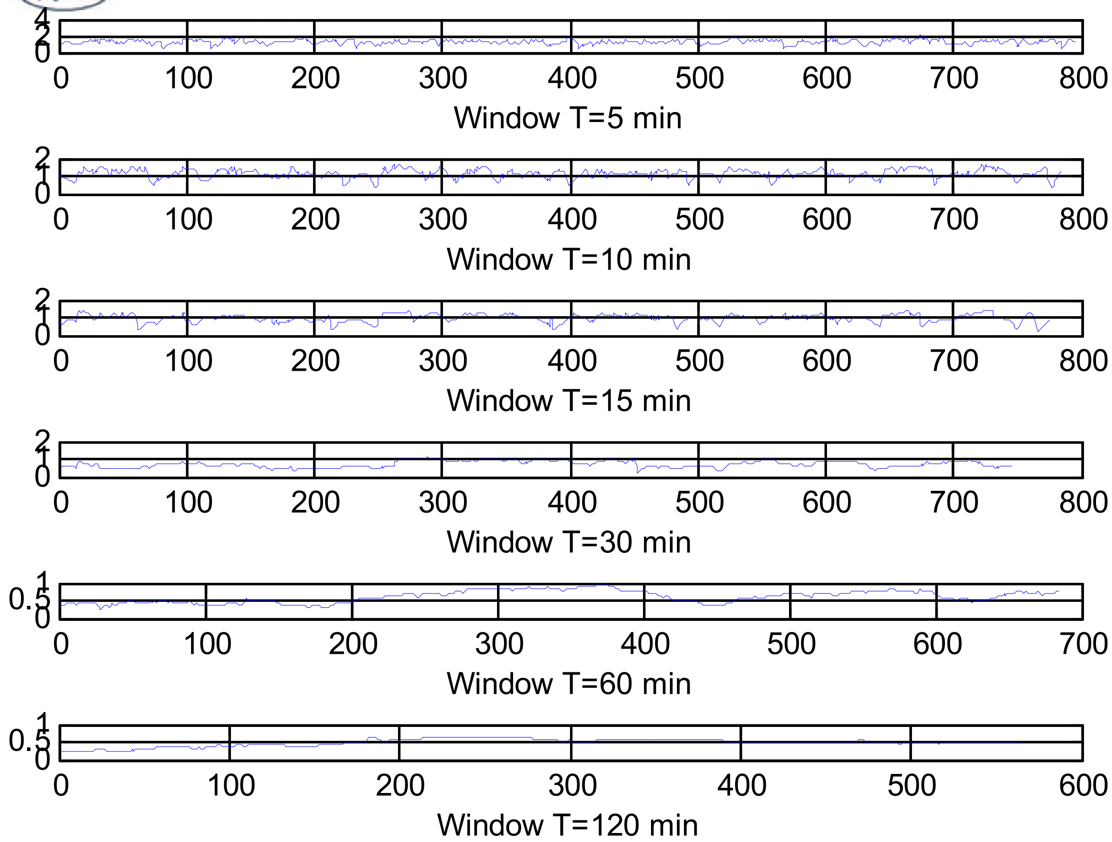
The raw signals containing all sleep stages were used “as is”, no preliminary selection and concatenation of sleep stages was made.

Testing MI for different settings-2

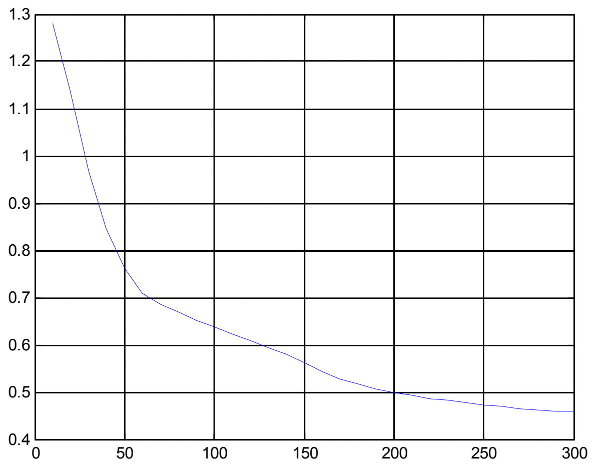


Testing MI for different settings-3

Time window



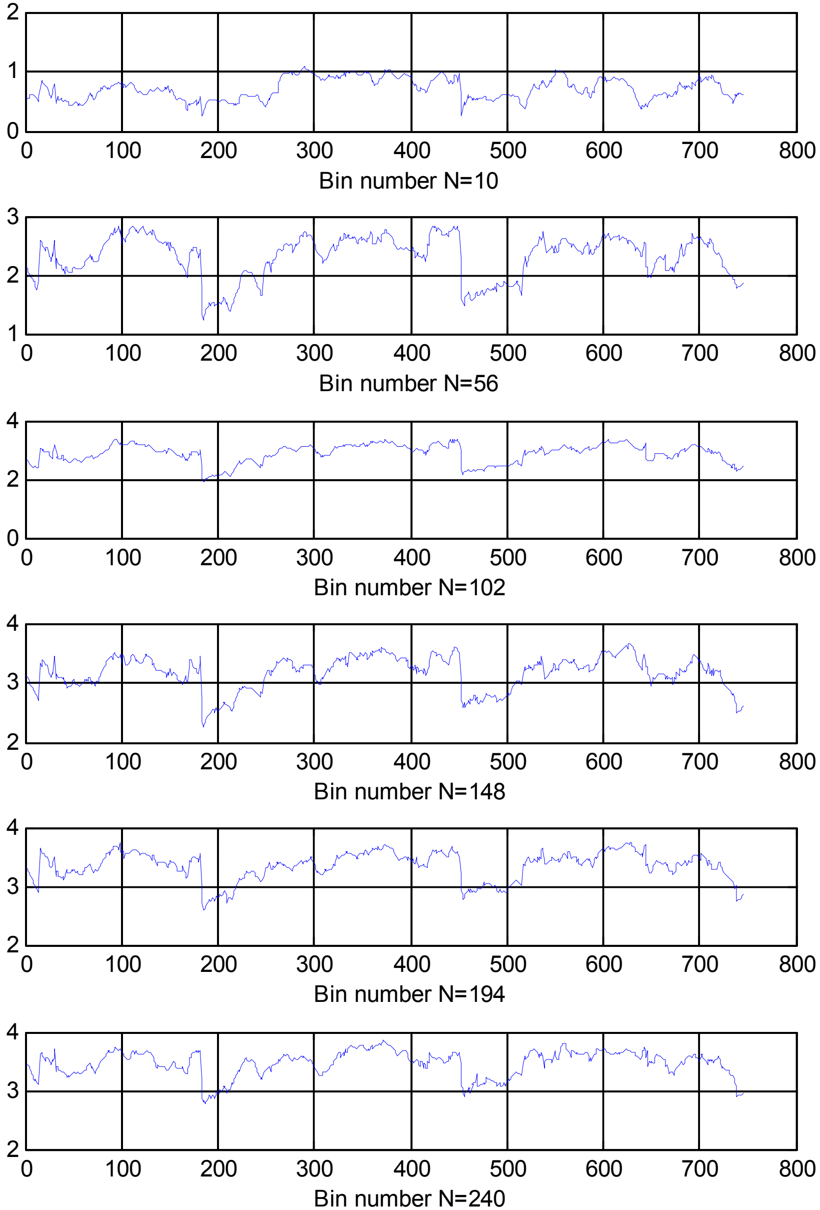
Window duration, min	Mean MI	STD MI
5	1,2792	0,2722
10	1,1377	0,2540
15	0,9661	0,2270
30	0,7098	0,1797
60	0,6094	0,1691
120	0,4774	0,1060

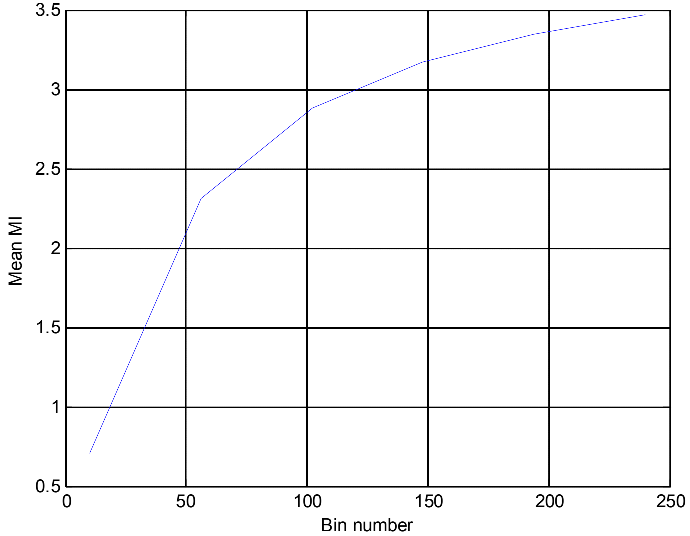


Analysis of fluctuations in can light the right window length for meaningful estimation of MI time course.
Decreasing of mean MI can be explained by presence of information transfer between two signals on shorter time intervals.

Testing MI for different settings-4

Bin number





The mean value increases but the shape of MMI is almost the same for different bin numbers.
Normalization technique can be used to avoid such dependence.

Measure of parameter usability for sleep scoring using MI - 1

The purpose – to derive the measure for selecting the HR parameters, most suitable for possible exploiting for sleep scoring.

The MI was calculated to find out between which processes the MI is maximal during the night.

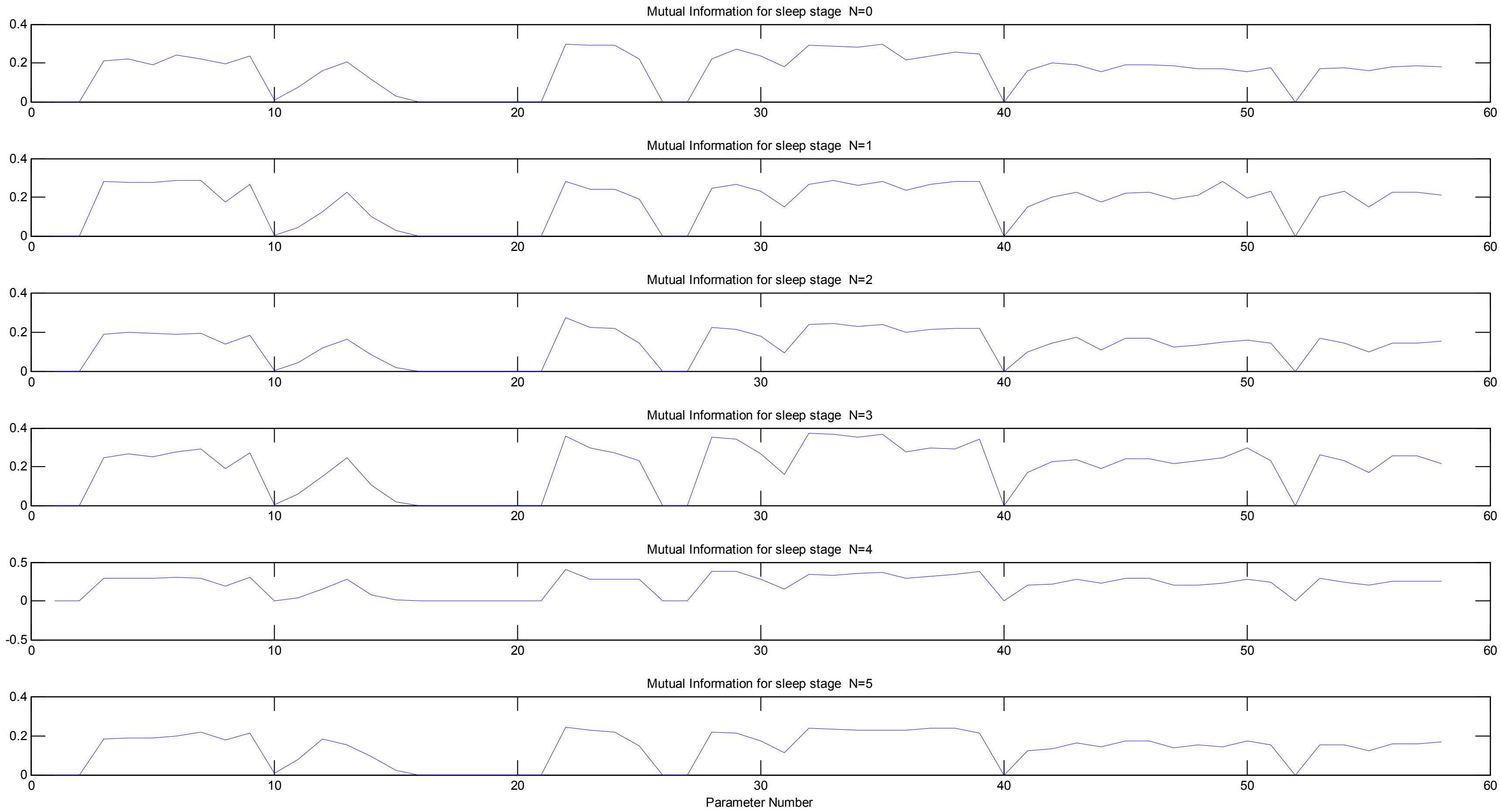
1. The pairs of signals were composed.
2. The parts with the same sleep stages were extracted from each signal and concatenated together.
3. The number of bins was calculated using the Scott's formula for bin size

$$h_n = 3{\cdot}49sn^{-1/3}$$

h_n – is the bin width,
s – estimate of standard deviation,
n – number of data samples in the signal.
This measure for bin width is more preferable than commonly used Sturges formula, because the later is developed with Parameteric Gaussian assumption.

Measure of parameter usability for sleep scoring using MI – results-1

General presentation of average MI between EEG and HR parameters for different sleep stages.



Measure of parameter usability for sleep scoring using MI – data-1

Delta-EEG vs *all HRV parameters*

Parameter name	Awake
22. meanNN	0,2983
35. renyi2	0,2939
23. sdNN	0,2921
32. Shannon	0,2908
24. cvNN	0,2886
33. renyi025	0,2879
34. renyi4	0,2829
29. pNN50	0,2703
38. pNNl30	0,2558
39. pNNl50	0,2475

Parameter name	1
33. renyi025	0,2883
6. FWRENYI4	0,2869
7. WSDVAR	0,2848
3. FORBWORD	0,2819
39. pNNl50	0,2819
38. pNNl30	0,2813
22. meanNN	0,2797
35. renyi2	0,2796
49. LFtoP	0,2786
4. FWSHANN	0,2783

Parameter name	2
22. meanNN	0,2742
33. renyi025	0,2406
32. Shannon	0,2385
35. renyi2	0,2354
34. renyi4	0,2260
23. sdNN	0,2229
28. rmssd	0,2211
39. pNNl50	0,2179
38. pNNl30	0,2164
24. cvNN	0,2151

Parameter name	3
32. Shannon	0,3726
35. renyi2	0,3694
33. renyi025	0,3667
22. meanNN	0,3575
28. rmssd	0,3506
34. renyi4	0,3501
39. pNNl50	0,3429
29. pNN50	0,3426
37. NNl20	0,2972
50. HFtoP	0,2955

Parameter name	4
22. meanNN	0,4026
29. pNN50	0,3819
39. pNNl50	0,3818
28. rmssd	0,3787
35. renyi2	0,3678
34. renyi4	0,3499
32. Shannon	0,3429
38. pNNl30	0,3388
33. renyi025	0,3263
37. NNl20	0,3163

Parameter name	REM
22. meanNN	0,2450
29. pNN50	0,2142
39. pNNl50	0,2135
28. rmssd	0,2193
35. renyi2	0,2275
34. renyi4	0,2260
32. Shannon	0,2360
38. pNNl30	0,2388
33. renyi025	0,2335
37. NNl20	0,2381

Measure of parameter usability for sleep scoring using MI – data-2

Theta-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,2947
39. pNNl50	0,2681
33. renyi025	0,2664
34. renyi4	0,2663
35. renyi2	0,2660
24. cvNN	0,2619
38. pNNl30	0,2601
32. Shannon	0,2569
29. pNN50	0,2525
9. WPSUM13	0,2480

Parameter name	1
22. meanNN	0,3155
7. WSDVAR	0,2878
6. FWRENYI4	0,2810
9. WPSUM13	0,2779
35. renyi2	0,2772
34. renyi4	0,2753
33. renyi025	0,2745
36. pNNl10	0,2743
4. FWSHANN	0,2628
32. Shannon	0,2627

Parameter name	2
22. meanNN	0,3015
28. rmssd	0,2374
39. pNNl50	0,2313
38. pNNl30	0,2261
29. pNN50	0,2253
35. renyi2	0,2251
33. renyi025	0,2245
32. Shannon	0,2236
23. sdNN	0,2221
34. renyi4	0,2197

Parameter name	3
22. meanNN	0,4064
32. Shannon	0,3463
28. rmssd	0,3398
38. pNNl30	0,3371
33. renyi025	0,3352
29. pNN50	0,3340
35. renyi2	0,3314
34. renyi4	0,3243
39. pNNl50	0,3186
37. NNl20	0,3170

Parameter name	4
22. meanNN	0,4464
39. pNNl50	0,3747
29. pNN50	0,3696
28. rmssd	0,3553
35. renyi2	0,3340
34. renyi4	0,3339
32. Shannon	0,3327
38. pNNl30	0,3097
37. NNl20	0,3016
33. renyi025	0,2983

Parameter name	REM
22. meanNN	0,2735
37. NNl20	0,2506
32. Shannon	0,2449
35. renyi2	0,2413
33. renyi025	0,2388
38. pNNl30	0,2368
39. pNNl50	0,2335
29. pNN50	0,2314
28. rmssd	0,2304
36. pNNl10	0,2298

Measure of parameter usability for sleep scoring using MI – data-3

Alpha-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,3065
33. renyi025	0,2934
24. cvNN	0,2758
32. Shannon	0,2754
35. renyi2	0,2741
34. renyi4	0,2563
39. pNNl50	0,2500
30. pNN100	0,2462
29. pNN50	0,2441
23. sdNN	0,2433

Parameter name	1
33. renyi025	0,3012
5. FWRENY25	0,2995
22. meanNN	0,2857
4. FWSHANN	0,2830
38. pNNl30	0,2828
29. pNN50	0,2788
6. FWRENYI4	0,2778
3. FORBWORD	0,2766
35. renyi2	0,2760
37. NNl20	0,2757

Parameter name	2
22. meanNN	0,2955
24. cvNN	0,2578
23. sdNN	0,2572
33. renyi025	0,2548
32. Shannon	0,2426
35. renyi2	0,2401
34. renyi4	0,2288
28. rmssd	0,2262
29. pNN50	0,2157
38. pNNl30	0,2147

Parameter name	3
22. meanNN	0,4285
32. Shannon	0,3878
35. renyi2	0,3672
33. renyi025	0,3654
34. renyi4	0,3620
28. rmssd	0,3514
24. cvNN	0,3361
38. pNNl30	0,3303
23. sdNN	0,3240
29. pNN50	0,3111

Parameter name	4
22. meanNN	0,4714
29. pNN50	0,3673
39. pNNl50	0,3544
32. Shannon	0,3492
38. pNNl30	0,3488
35. renyi2	0,3469
28. rmssd	0,3349
37. NNl20	0,3303
33. renyi025	0,3300
34. renyi4	0,3252

Parameter name	REM
24. cvNN	0,2795
23. sdNN	0,2546
32. Shannon	0,2472
22. meanNN	0,2459
35. renyi2	0,2445
28. rmssd	0,2443
33. renyi025	0,2441
34. renyi4	0,2267
37. NNl20	0,2212
29. pNN50	0,2183

Measure of parameter usability for sleep scoring using MI – data-4

Beta-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,3390
34. renyi4	0,2903
24. cvNN	0,2871
33. renyi025	0,2781
35. renyi2	0,2755
23. sdNN	0,2738
32. Shannon	0,2735
6. FWRENYI4	0,2524
39. pNNl50	0,2488
4. FWSHANN	0,2440

Parameter name	1
23. sdNN	0,3177
24. cvNN	0,3102
22. meanNN	0,3050
33. renyi025	0,2925
32. Shannon	0,2801
3. FORBWORD	0,2799
34. renyi4	0,2707
35. renyi2	0,2681
38. pNNl30	0,2679
6. FWRENYI4	0,2608

Parameter name	2
24. cvNN	0,3527
23. sdNN	0,3431
32. Shannon	0,3216
33. renyi025	0,3208
35. renyi2	0,3057
22. meanNN	0,3028
34. renyi4	0,2820
25. sdaNN1	0,2628
28. rmssd	0,2516
53. allLFtoP	0,2301

Parameter name	3
32. Shannon	0,3676
33. renyi025	0,3574
24. cvNN	0,3476
22. meanNN	0,3441
35. renyi2	0,3439
23. sdNN	0,3418
34. renyi4	0,3261
25. sdaNN1	0,3180
28. rmssd	0,2844
51. VLFtoP	0,2756

Parameter name	4
22. meanNN	0,4093
33. renyi025	0,3367
32. Shannon	0,3329
28. rmssd	0,3207
39. pNNl50	0,3173
35. renyi2	0,3159
29. pNN50	0,3111
23. sdNN	0,3034
24. cvNN	0,3004
25. sdaNN1	0,2978

Parameter name	REM
24. cvNN	0,2938
23. sdNN	0,2766
33. renyi025	0,2709
32. Shannon	0,2682
35. renyi2	0,2590
34. renyi4	0,2394
28. rmssd	0,2365
22. meanNN	0,2336
29. pNN50	0,2168
38. pNNl30	0,2076

Measure of parameter usability for sleep scoring using MI – data-5

Beta/Delta-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,3119
39. pNNl50	0,2540
33. renyi025	0,2523
38. pNNl30	0,2510
37. NNl20	0,2391
32. Shannon	0,2387
28. rmssd	0,2371
29. pNN50	0,2366
35. renyi2	0,2329
34. renyi4	0,2327

Parameter name	1
22. meanNN	0,2959
33. renyi025	0,2840
24. cvNN	0,2824
23. sdNN	0,2817
34. renyi4	0,2781
32. Shannon	0,2763
35. renyi2	0,2720
51. VLFtoP	0,2577
54. UV_LFtoP	0,2577
29. pNN50	0,2488

Parameter name	2
23. sdNN	0,3044
24. cvNN	0,2991
32. Shannon	0,2938
35. renyi2	0,2891
22. meanNN	0,2868
34. renyi4	0,2787
33. renyi025	0,2779
25. sdaNN1	0,2463
28. rmssd	0,2355
53. allLFtoP	0,2149

Parameter name	3
23. sdNN	0,3813
24. cvNN	0,3800
32. Shannon	0,3670
33. renyi025	0,3610
35. renyi2	0,3452
25. sdaNN1	0,3342
34. renyi4	0,3146
22. meanNN	0,2754
28. rmssd	0,2732
53. allLFtoP	0,2730

Parameter name	4
33. renyi025	0,3409
22. meanNN	0,3382
24. cvNN	0,3371
23. sdNN	0,3362
32. Shannon	0,3362
35. renyi2	0,3359
25. sdaNN1	0,3266
34. renyi4	0,3228
28. rmssd	0,3027
39. pNNl50	0,2881

Parameter name	REM
24. cvNN	0,3240
33. renyi025	0,3065
23. sdNN	0,3032
32. Shannon	0,2968
35. renyi2	0,2845
34. renyi4	0,2713
28. rmssd	0,2566
22. meanNN	0,2559
38. pNNl30	0,2311
29. pNN50	0,2216

Measure of parameter usability for sleep scoring using MI – data-6

Beta/Theta-EEG vs *all HRV parameters*

Parameter name	Awake
22. meanNN	0,3129
24. cvNN	0,2607
34. renyi4	0,2518
35. renyi2	0,2472
23. sdNN	0,2399
6. FWRENYI4	0,2379
39. pNNl50	0,2351
33. renyi025	0,2346
29. pNN50	0,2331
32. Shannon	0,2321

Parameter name	1
24. cvNN	0,3154
23. sdNN	0,3028
34. renyi4	0,2813
35. renyi2	0,2798
33. renyi025	0,2794
51. VLFtoP	0,2746
54. UV_LFtoP	0,2746
22. meanNN	0,2729
32. Shannon	0,2667
25. sdaNN1	0,2580

Parameter name	2
23. sdNN	0,3094
24. cvNN	0,3038
32. Shannon	0,2898
35. renyi2	0,2879
33. renyi025	0,2806
22. meanNN	0,2763
34. renyi4	0,2662
25. sdaNN1	0,2432
28. rmssd	0,2427
53. allLFtoP	0,2163

Parameter name	3
23. sdNN	0,3563
24. cvNN	0,3493
32. Shannon	0,3450
25. sdaNN1	0,3289
33. renyi025	0,3285
35. renyi2	0,3279
34. renyi4	0,3059
53. allLFtoP	0,2878
51. VLFtoP	0,2776
54. UV_LFtoP	0,2776

Parameter name	4
22. meanNN	0,3494
32. Shannon	0,3157
34. renyi4	0,3140
35. renyi2	0,3128
23. sdNN	0,3126
25. sdaNN1	0,3119
33. renyi025	0,3114
24. cvNN	0,3072
28. rmssd	0,2760
39. pNNl50	0,2595

Parameter name	REM
24. cvNN	0,2992
23. sdNN	0,2804
33. renyi025	0,2731
32. Shannon	0,2611
35. renyi2	0,2591
22. meanNN	0,2474
34. renyi4	0,2396
28. rmssd	0,2376
25. sdaNN1	0,2151
29. pNN50	0,1994

Measure of parameter usability for sleep scoring using MI – data-7

Beta/Alpha-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,2928
33. renyi025	0,2672
35. renyi2	0,2623
32. Shannon	0,2623
24. cvNN	0,2574
34. renyi4	0,2553
39. pNNl50	0,2544
23. sdNN	0,2456
29. pNN50	0,2449
38. pNNl30	0,2355

Parameter name	1
22. meanNN	0,3154
33. renyi025	0,3060
23. sdNN	0,2978
7. WSDVAR	0,2894
32. Shannon	0,2873
35. renyi2	0,2838
34. renyi4	0,2760
24. cvNN	0,2750
9. WPSUM13	0,2729
5. FWRENY25	0,2718

Parameter name	2
22. meanNN	0,2810
24. cvNN	0,2532
23. sdNN	0,2521
32. Shannon	0,2435
35. renyi2	0,2419
33. renyi025	0,2375
34. renyi4	0,2307
28. rmssd	0,2115
39. pNNl50	0,1977
38. pNNl30	0,1963

Parameter name	3
33. renyi025	0,3302
32. Shannon	0,3217
22. meanNN	0,3195
23. sdNN	0,3185
24. cvNN	0,3118
35. renyi2	0,3046
25. sdaNN1	0,2969
34. renyi4	0,2836
51. VLFtoP	0,2670
54. UV_LFtoP	0,2670

Parameter name	4
22. meanNN	0,3398
33. renyi025	0,3084
32. Shannon	0,3074
35. renyi2	0,3044
39. pNNl50	0,3025
34. renyi4	0,2971
23. sdNN	0,2894
28. rmssd	0,2872
29. pNN50	0,2857
24. cvNN	0,2851

Parameter name	REM
33. renyi025	0,2749
24. cvNN	0,2745
32. Shannon	0,2705
23. sdNN	0,2671
35. renyi2	0,2535
22. meanNN	0,2382
34. renyi4	0,2352
28. rmssd	0,2341
38. pNNl30	0,2167
37. NNl20	0,2117

Measure of parameter usability for sleep scoring using MI – data-8

Alpha/Delta-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,2890
39. pNNl50	0,2606
33. renyi025	0,2492
32. Shannon	0,2457
29. pNN50	0,2448
35. renyi2	0,2393
38. pNNl30	0,2344
34. renyi4	0,2262
9. WPSUM13	0,2248
28. rmssd	0,2220

Parameter name	1
22. meanNN	0,2819
33. renyi025	0,2776
39. pNNl50	0,2732
32. Shannon	0,2720
34. renyi4	0,2546
6. FWRENYI4	0,2541
35. renyi2	0,2539
29. pNN50	0,2537
28. rmssd	0,2501
24. cvNN	0,2483

Parameter name	2
23. sdNN	0,2675
33. renyi025	0,2665
32. Shannon	0,2633
24. cvNN	0,2587
22. meanNN	0,2556
35. renyi2	0,2499
34. renyi4	0,2438
28. rmssd	0,2119
25. sdaNN1	0,2017
37. NNl20	0,2008

Parameter name	3
35. renyi2	0,3436
32. Shannon	0,3419
33. renyi025	0,3278
23. sdNN	0,3255
24. cvNN	0,3223
34. renyi4	0,3130
28. rmssd	0,3024
22. meanNN	0,3017
25. sdaNN1	0,2822
53. allLFtoP	0,2795

Parameter name	4
22. meanNN	0,3505
35. renyi2	0,3340
34. renyi4	0,3253
32. Shannon	0,3201
23. sdNN	0,3074
33. renyi025	0,3068
24. cvNN	0,3012
25. sdaNN1	0,2950
28. rmssd	0,2936
39. pNNl50	0,2661

Parameter name	REM
24. cvNN	0,2574
23. sdNN	0,2564
35. renyi2	0,2453
32. Shannon	0,2443
33. renyi025	0,2384
34. renyi4	0,2338
22. meanNN	0,2302
28. rmssd	0,2199
37. NNl20	0,2130
38. pNNl30	0,2102

Measure of parameter usability for sleep scoring using MI – data-9

Alpha/Theta-EEG **vs** *all HRV parameters*

Parameter name	Awake
22. meanNN	0,2992
33. renyi025	0,2521
29. pNN50	0,2489
39. pNNl50	0,2457
24. cvNN	0,2278
35. renyi2	0,2271
30. pNN100	0,2262
23. sdNN	0,2229
32. Shannon	0,2193
38. pNNl30	0,2188

Parameter name	1
6. FWRENYI4	0,2908
22. meanNN	0,2874
29. pNN50	0,2838
7. WSDVAR	0,2762
9. WPSUM13	0,2758
39. pNNl50	0,2727
5. FWRENY25	0,2645
37. NNl20	0,2630
4. FWSHANN	0,2609
33. renyi025	0,2597

Parameter name	2
24. cvNN	0,2733
23. sdNN	0,2714
32. Shannon	0,2697
22. meanNN	0,2648
33. renyi025	0,2627
35. renyi2	0,2562
34. renyi4	0,2401
28. rmssd	0,2254
25. sdaNN1	0,2143
53. allLFtoP	0,2036

Parameter name	3
32. Shannon	0,3636
35. renyi2	0,3626
33. renyi025	0,3539
34. renyi4	0,3482
24. cvNN	0,3463
22. meanNN	0,3449
23. sdNN	0,3428
28. rmssd	0,3213
53. allLFtoP	0,3025
25. sdaNN1	0,2875

Parameter name	4
22. meanNN	0,3631
34. renyi4	0,3161
32. Shannon	0,3157
35. renyi2	0,3121
33. renyi025	0,3027
23. sdNN	0,2940
24. cvNN	0,2901
37. NNl20	0,2851
25. sdaNN1	0,2812
28. rmssd	0,2721

Parameter name	REM
24. cvNN	0,2866
23. sdNN	0,2858
33. renyi025	0,2673
32. Shannon	0,2659
35. renyi2	0,2559
28. rmssd	0,2484
22. meanNN	0,2476
34. renyi4	0,2427
37. NNl20	0,2194
36. pNNl10	0,2169

Measure of parameter usability for sleep scoring using MI – data-10

Theta/Delta-EEG **vs** *all HRV parameters*

Parameter name	Awake
33. renyi025	0,3012
22. meanNN	0,2977
32. Shannon	0,2697
23. sdNN	0,2686
35. renyi2	0,2627
24. cvNN	0,2581
39. pNNl50	0,2545
38. pNNl30	0,2515
29. pNN50	0,2468
34. renyi4	0,2445

Parameter name	1
38. pNNl30	0,3188
4. FWSHANN	0,3168
22. meanNN	0,3156
39. pNNl50	0,3004
7. WSDVAR	0,2979
5. FWRENY25	0,2960
6. FWRENYI4	0,2949
36. pNNl10	0,2947
33. renyi025	0,2882
37. NNl20	0,2879

Parameter name	2
22. meanNN	0,2771
35. renyi2	0,2537
32. Shannon	0,2528
23. sdNN	0,2467
34. renyi4	0,2429
33. renyi025	0,2428
24. cvNN	0,2423
38. pNNl30	0,2298
37. NNl20	0,2226
28. rmssd	0,2138

Parameter name	3
32. Shannon	0,3480
35. renyi2	0,3340
33. renyi025	0,3314
34. renyi4	0,3165
28. rmssd	0,3135
22. meanNN	0,3038
23. sdNN	0,2917
29. pNN50	0,2894
24. cvNN	0,2869
39. pNNl50	0,2838

Parameter name	4
35. renyi2	0,3304
34. renyi4	0,3270
32. Shannon	0,3268
28. rmssd	0,3130
22. meanNN	0,3125
23. sdNN	0,3043
33. renyi025	0,3042
24. cvNN	0,3001
29. pNN50	0,2823
39. pNNl50	0,2723

Parameter name	REM
22. meanNN	0,2317
33. renyi025	0,2243
24. cvNN	0,2206
23. sdNN	0,2205
36. pNNl10	0,2164
34. renyi4	0,2158
4. FWSHANN	0,2102
32. Shannon	0,2100
35. renyi2	0,2069
37. NNl20	0,2064

Measure of parameter usability for sleep scoring using MI – results-1

EEG-parameter	Awake	1	2	3	4	REM
1. Delta	22. meanNN	33. renyi025	22. meanNN	32. Shannon	22. meanNN	22. meanNN
2. Theta	22. meanNN	22. meanNN	22. meanNN	22. meanNN	22. meanNN	22. meanNN
3. Alpha	22. meanNN	33. renyi025	22. meanNN	22. meanNN	22. meanNN	24. cvNN
4. Beta	22. meanNN	23. sdNN	24. cvNN	32. Shannon	22. meanNN	24. cvNN
5. Beta/Delta	22. meanNN	22. meanNN	23. sdNN	23. sdNN	33. renyi025	24. cvNN
6. Beta/Theta	22. meanNN	24. cvNN	23. sdNN	23. sdNN	22. meanNN	24. cvNN
7. Beta/Alpha	22. meanNN	22. meanNN	22. meanNN	33. renyi025	22. meanNN	33. renyi025
8. Alpha/Delta	22. meanNN	22. meanNN	23. sdNN	35. renyi2	22. meanNN	24. cvNN
9. Alpha/Theta	22. meanNN	6. FWRENYI4	24. cvNN	32. Shannon	22. meanNN	24. cvNN
10. Theta/Delta	33. renyi025	38. pNNl30	22. meanNN	32. Shannon	35. renyi2	22. meanNN

For different sleep stages the overwhelming majority of parameters are simple statistical: meanNN, sdNN, cvNN. Also there are some entropy parameters: Renyi and Shannon entropies.
No frequency parameters appear in top of the list.

Measure of parameter usability for sleep scoring using MI - 2

The second set of experiments

The MI was calculated to find out between which processes the MI is maximal during the night.

1. The pairs of signals were composed.
2. The raw signals containing all sleep stages were used “as is”, no preliminary selection and concatenation of sleep stages was made.

Measure of parameter usability for sleep scoring using MI – data-11

Delta EEG

Parameter name	MI
22. meanNN	0,3259
33. renyi025	0,2739
23. sdNN	0,2675
32. Shannon	0,2659
24. cvNN	0,2649
35. renyi2	0,2607
28. rmssd	0,2538
39. pNNl50	0,2532
38. pNNl30	0,2486
29. pNN50	0,2483

Theta EEG

Parameter name	MI
22. meanNN	0,3479
33. renyi025	0,2675
28. rmssd	0,2671
23. sdNN	0,2624
32. Shannon	0,2623
39. pNNl50	0,2582
24. cvNN	0,2566
29. pNN50	0,2537
35. renyi2	0,2536
38. pNNl30	0,2512

Alpha EEG

Parameter name	MI
22. meanNN	0,3169
24. cvNN	0,2813
23. sdNN	0,2768
33. renyi025	0,2688
32. Shannon	0,2629
35. renyi2	0,2593
34. renyi4	0,2497
38. pNNl30	0,2489
28. rmssd	0,2460
37. NNl20	0,2325

Beta EEG

Parameter name	MI
24. cvNN	0,3645
23. sdNN	0,3485
22. meanNN	0,3343
32. Shannon	0,3128
33. renyi025	0,3118
35. renyi2	0,3049
34. renyi4	0,2886
25. sdaNN1	0,2667
28. rmssd	0,2501
53. allLFtoP	0,2274

Beta/Delta EEG

Parameter name	MI
24. cvNN	0,3283
23. sdNN	0,3152
22. meanNN	0,3043
32. Shannon	0,2997
33. renyi025	0,2930
35. renyi2	0,2928
34. renyi4	0,2788
25. sdaNN1	0,2633
28. rmssd	0,2407
53. allLFtoP	0,2306

Beta/Theta EEG

Parameter name	MI
24. cvNN	0,3328
23. sdNN	0,3207
22. meanNN	0,3065
32. Shannon	0,2912
35. renyi2	0,2869
33. renyi025	0,2852
34. renyi4	0,2704
25. sdaNN1	0,2599
28. rmssd	0,2515
53. allLFtoP	0,2135

Measure of parameter usability for sleep scoring using MI – data-12

Beta/Alpha EEG

Parameter name	MI
22. meanNN	0,3064
24. cvNN	0,2763
23. sdNN	0,2642
32. Shannon	0,2479
35. renyi2	0,2477
33. renyi025	0,2450
34. renyi4	0,2348
28. rmssd	0,2323
39. pNNl50	0,2171
38. pNNl30	0,2167

Alpha/Delta EEG

Parameter name	MI
24. cvNN	0,2770
23. sdNN	0,2674
22. meanNN	0,2606
32. Shannon	0,2558
33. renyi025	0,2546
35. renyi2	0,2493
34. renyi4	0,2372
25. sdaNN1	0,2135
28. rmssd	0,2040
53. allLFtoP	0,1994

Alpha/Theta EEG

Parameter name	MI
22. meanNN	0,2887
24. cvNN	0,2812
23. sdNN	0,2699
33. renyi025	0,2544
32. Shannon	0,2541
35. renyi2	0,2465
34. renyi4	0,2332
28. rmssd	0,2239
25. sdaNN1	0,2112
38. pNNl30	0,1996

Theta/Delta EEG

Parameter name	MI
22. meanNN	0,3222
24. cvNN	0,2986
23. sdNN	0,2913
32. Shannon	0,2846
33. renyi025	0,2814
35. renyi2	0,2805
34. renyi4	0,2705
38. pNNl30	0,2623
28. rmssd	0,2552
37. NNl20	0,2478

Occurrences of parameters in Top-5

Parameter name	N
22. meanNN	10
23. sdNN	10
32. Shannon	10
24. cvNN	9
33. renyi025	8
35. renyi2	2
28. rmssd	1

MI - Conclusions

1. From the point of view of Mutual Information, several parameters are most coupled with brain electrical activity, namely meanNN, sdNN, cvNN and entropies.

2. There is almost no difference in the most coupled parameters for the case of concatenated signals and raw signals. This could mean that MI characteristics are similar throughout the signal for each sleep stage.

3. There are completely no frequency parameters in the top of selected by the MI approach. This could mean that (1) there is no substantial statistical coupling, (2) the parameters of MI calculation are not appropriate for catching the coupling with frequency parameters, (3) the way the frequency parameters were calculated is not appropriate.

4. Substantial MI between two variables doesn’t imply the presence of any coupling between two systems. Its only statistical measure.

MI - Open problems and Future work-1

1. We need to find a way to avoid the requirement of stationarity and ergodicity of stochastic processes. The work on introducing a new dynamical measure of mutual information should be started.

2. We need to find a way to select stationary parts of a signals to use them for analysis. Changes in signals from time to time during sleep stage changes are definitely introduce nonstationarities in a signal.

3. The technique for assuring stationarity of the parts taken from the signal should be developed, or special segmentation procedure should be preliminary employed.

4. Its interesting to check the differences in MI comparing with surrogate data.

5. It may happen that MI is large and calculated “information transfer” is substantial in value. But there is no evidence in this measure that this information is really “flows” from one process to another. Even in this case its possible that two independent time series simply have the statistical characteristics (e.g. MI) such that our MI measure is large. True drive-response coupling in time is still unclear.

MI - Open problems and Future work-2

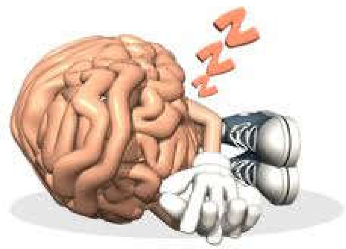
6. A better results are expected if raw data are available. This allows to recalculate the EEG and HRV parameters and coupling measures with larger flexibility and with different settings.

7. Conditional MI and Permutation MI should be further used for detecting the direction of coupling between two signals.

8. MI has strong dependence on the window length, thus the method for selecting the length should be developed.

9. The concatenation of parts of the signal from different stages could be possible only if (1) the statistical parameters of sleep stages from different sleep cycles are the same, (2) if boarder effects on the beginning and the end of the stage could be neglected, (3) if there are no substantial and/or meaningful changes in the characteristics of signals during the night.

Phase Synchronization



Phase synchronization approach

Is used for analyzing non-linear interdependencies in signals and focuses on the phases of signals.

Recent studies show that even if the amplitudes of chaotic-like signals are uncorrelated, their phases may change synchronously.

One of the robust measure of PS is **phase-locking value (PLV).**

PLV is the method to estimate instantaneous phase relationship between two signals and to detect synchrony in phases in precise frequency range.

Given two series ***x*** and ***y*** and a frequency of interest ***f***, we need to estimate for each latency the measure of phase-locking between components of ***x*** and ***y*** at frequency ***f***. For estimating phase-locking we need to extract instantaneous phases of each time series.

There are three main approaches to PLV computation:

- Using wavelet functions and filtration
- Using Hilbert transform
- Using Mutual Information

Phase Locking Value-1

1. Wavelet convolution

-Given two time series, band-pass filter each with FIR filter with central frequency ***f***.

-Compute the **convolution** with a complex Gabor wavelet centered at frequency ***f***.

$$G(t, f) = \exp\left(-\frac{t^2}{2\sigma_t^2}\right)\exp\{j2\pi ft\}$$

-The **phase** $\phi(t, n)$ of this convolution is extracted for all time instances ***t*** and for each of ***n*** trials.

-**PLV** is defined as

$$PLV_t = \frac{1}{N}\left|\sum_{n=1}^{N} \exp\,(j\theta(t, n))\right|$$

where $\theta(t, n)$ is the phase difference $\phi_1(t, n) - \phi_2(t, n)$

PLV measures variability of phase differences across trials, if it is close to 1 then phase differences vary little, otherwise it is close to zero.

- Statistical **testing** based on surrogate data for differentiating significant PLV against background fluctuations.

Phase Locking Value-2

2. Hilbert transform

- For each time series analytical signal H(t) is computed as

$$H(t) = x(t) + i\tilde{x}(t)$$

where $\tilde{x}(t)$ is Hilbert transform of $x(t)$, defined as

$$\tilde{x}(t) = \frac{1}{\pi}\mathrm{PV}\int_{-\infty}^{\infty}\frac{x(t')}{t-t'}dt'$$

- the instantaneous phase of analytical signal is defined as

$$\phi(t) = \arctan\frac{\tilde{x}(t)}{x(t)}$$

-PLV metric is defined as

$$\mathrm{PLV} = \left|\frac{1}{N}\sum_{j=0}^{N-1} e^{i(\phi_X(j\Delta t)-\phi_Y(j\Delta t))}\right|$$

Phase Locking Value-3

3. Mutual Information

- For each time series Short-Time Fourier Transform is computed

-The Phase Spectra is extracted for each spectra

- Mutual Information between two Phase Spectra is calculated

Measure of parameter usability for sleep scoring using PS - 1

The purpose – to derive the measure for selecting the HR parameters, most suitable for possible exploiting for sleep scoring.

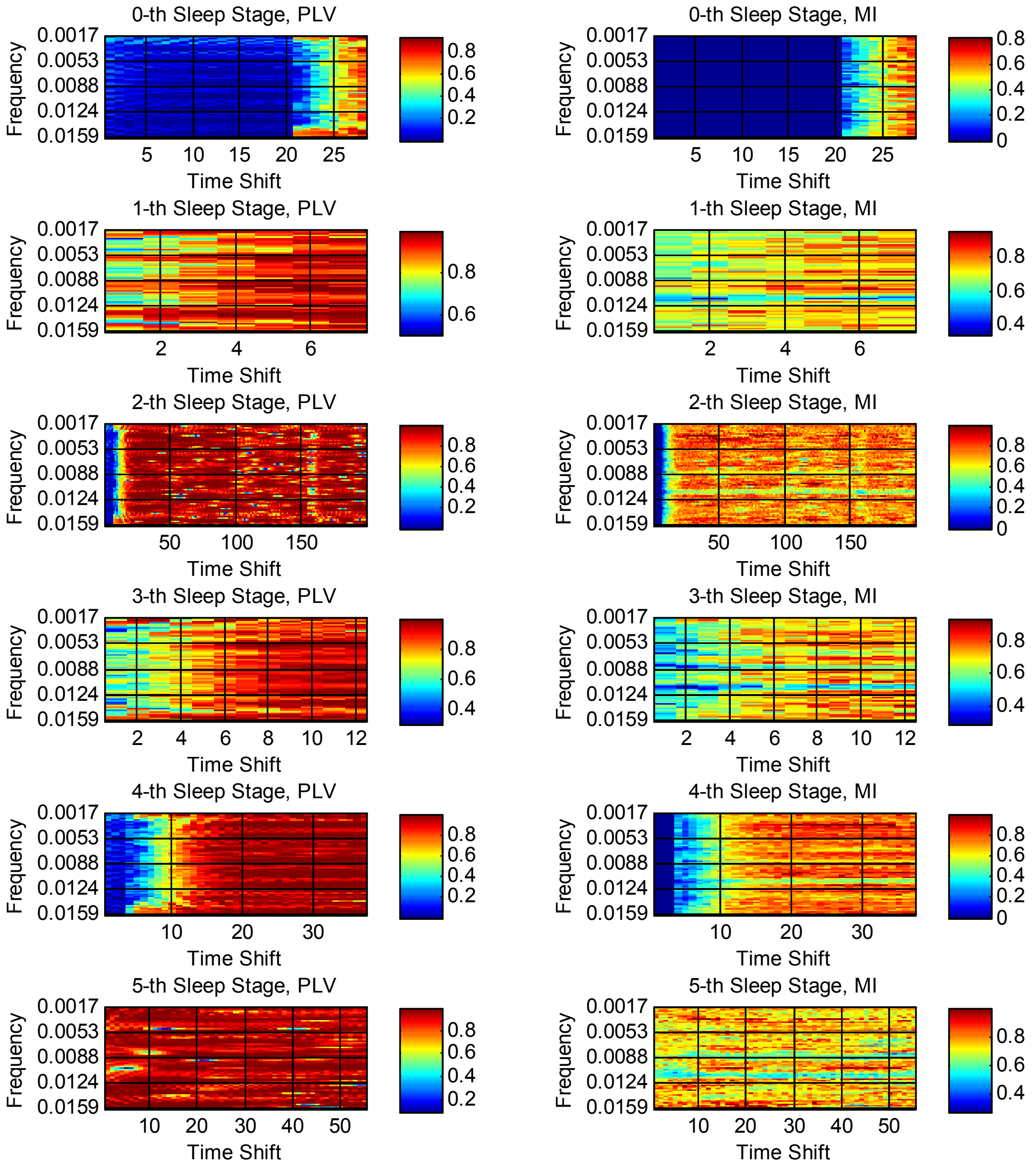
The PS was estimated by two techniques (PLV by **Hilbert transform** and by **MI approach**) to find out between which processes the PS is maximal during the night.

1. The pairs of signals were composed.
2. The raw signals containing all sleep stages were used “as is”, no preliminary selection and concatenation of sleep stages was made.
3. As a **measure of parameter quality** using of relative area of PLV plot, for which the PS is larger than a threshold is proposed.

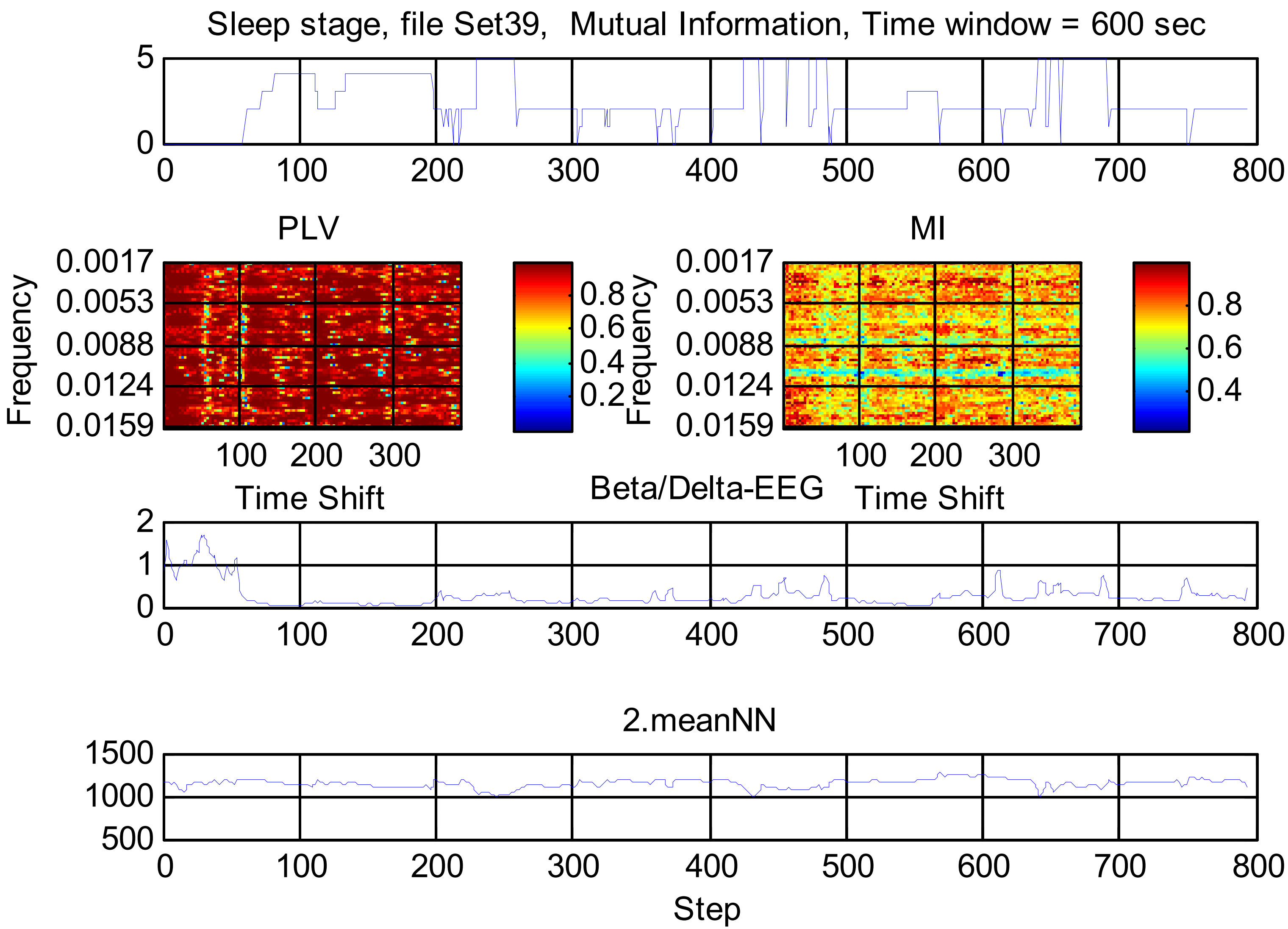
$$Q = \frac{plot\ area\ where\ PLV > Th}{total\ plot\ area} \times 100\%$$

4. In a first experiment, the mean value of PS for all PLV data is used as a threshold. In the second – the same but for surrogate data.

Measure of parameter usability for sleep scoring using PS



Measure of parameter usability for sleep scoring using PS



Measure of parameter usability for sleep scoring using PS – data-1

Delta

Parametr name	PS PLV Hilbert
22. meanNN	68,86%
31. pNN200	68,78%
39. pNNl50	68,61%
30. pNN100	68,60%
5. FWRENY25	68,54%
4. FWSHANN	68,48%
33. renyi025	68,47%
32. Shannon	68,47%
23. sdNN	68,45%
29. pNN50	68,44%

Parametr name	PS MI
31. pNN200	55,08%
30. pNN100	52,54%
41. VLF	52,29%
55. UVLF	52,29%
44. XF	52,09%
42. LF	52,05%
47. P	51,89%
48. LFtoHF	51,81%
23. sdNN	51,78%
51. VLFtoP	51,74%

Theta

Parametr name	PS PLV Hilbert
22. meanNN	69,02%
31. pNN200	68,90%
30. pNN100	68,72%
39. pNNl50	68,72%
5. FWRENY25	68,71%
24. cvNN	68,65%
35. renyi2	68,65%
4. FWSHANN	68,64%
34. renyi4	68,61%
32. Shannon	68,60%

Parametr name	PS MI
31. pNN200	55,13%
30. pNN100	52,57%
51. VLFtoP	52,09%
54. UV_LFtoP	52,09%
42. LF	52,04%
44. XF	51,89%
45. YF	51,88%
46. ZF	51,88%
58. noNNtime	51,85%
43. HF	51,85%

Measure of parameter usability for sleep scoring using PS – data-1

Alpha

Parametr name	PS PLV Hilbert
22. meanNN	69,45%
32. Shannon	69,26%
24. cvNN	69,21%
35. renyi2	69,20%
23. sdNN	69,19%
33. renyi025	69,14%
31. pNN200	69,05%
34. renyi4	69,01%
30. pNN100	68,82%
28. rmssd	68,76%

Parametr name	PS MI
31. pNN200	55,22%
30. pNN100	52,50%
46. ZF	51,99%
49. LFtoP	51,98%
44. XF	51,96%
57. HFn	51,94%
45. YF	51,91%
41. VLF	51,90%
55. UVLF	51,90%
50. HFtoP	51,90%

Beta-EEG

Parametr name	PS PLV Hilbert
22. meanNN	70,60%
24. cvNN	70,04%
23. sdNN	69,92%
32. Shannon	69,48%
35. renyi2	69,39%
31. pNN200	69,37%
33. renyi025	69,36%
25. sdaNN1	69,30%
34. renyi4	69,13%
28. rmssd	68,88%

Parametr name	PS MI
31. pNN200	55,28%
30. pNN100	52,71%
22. meanNN	52,61%
50. HFtoP	52,23%
49. LFtoP	52,13%
29. pNN50	52,08%
3. FORBWORD	52,00%
41. VLF	51,97%
55. UVLF	51,97%
45. YF	51,96%

Measure of parameter usability for sleep scoring using PS – data-1

Beta/Delta

Parametr name	PS PLV Hilbert
22. meanNN	69,71%
24. cvNN	69,45%
23. sdNN	69,35%
31. pNN200	69,28%
25. sdaNN1	69,02%
32. Shannon	69,00%
35. renyi2	68,98%
33. renyi025	68,91%
28. rmssd	68,85%
30. pNN100	68,85%

Parametr name	PS MI
31. pNN200	55,42%
30. pNN100	52,81%
22. meanNN	52,45%
50. HFtoP	52,42%
49. LFtoP	52,29%
58. noNNtime	52,23%
42. LF	52,21%
48. LFtoHF	52,16%
29. pNN50	52,12%
56. LFn	52,09%

Beta/Theta

Parametr name	PS PLV Hilbert
22. meanNN	70,19%
24. cvNN	69,75%
23. sdNN	69,62%
31. pNN200	69,38%
35. renyi2	69,27%
32. Shannon	69,25%
25. sdaNN1	69,19%
33. renyi025	69,11%
34. renyi4	69,03%
28. rmssd	68,99%

Parametr name	PS MI
31. pNN200	55,26%
30. pNN100	52,79%
22. meanNN	52,58%
58. noNNtime	52,25%
50. HFtoP	52,22%
3. FORBWORD	52,18%
57. HFn	52,13%
44. XF	52,07%
49. LFtoP	52,03%
42. LF	52,01%

Measure of parameter usability for sleep scoring using PS – data-1

Beta/Alpha

Parametr name	PS PLV Hilbert
22. meanNN	69,33%
31. pNN200	69,13%
24. cvNN	68,93%
23. sdNN	68,91%
32. Shannon	68,83%
35. renyi2	68,73%
28. rmssd	68,72%
30. pNN100	68,70%
33. renyi025	68,62%
34. renyi4	68,61%

Parametr name	PS MI
31. pNN200	55,52%
30. pNN100	52,90%
44. XF	52,49%
48. LFtoHF	52,24%
42. LF	52,10%
50. HFtoP	52,09%
22. meanNN	52,03%
57. HFn	51,99%
47. P	51,98%
56. LFn	51,98%

Alpha/Delta

Parametr name	PS PLV Hilbert
31. pNN200	69,00%
22. meanNN	68,88%
24. cvNN	68,65%
23. sdNN	68,64%
30. pNN100	68,62%
32. Shannon	68,60%
35. renyi2	68,56%
28. rmssd	68,54%
5. FWRENY25	68,54%
33. renyi025	68,52%

Parametr name	PS MI
31. pNN200	55,64%
30. pNN100	53,06%
49. LFtoP	52,57%
48. LFtoHF	52,47%
58. noNNtime	52,42%
57. HFn	52,40%
41. VLF	52,32%
55. UVLF	52,32%
53. allLFtoP	52,30%
43. HF	52,30%

Measure of parameter usability for sleep scoring using PS – data-1

Alpha/Theta

Parametr name	PS PLV Hilbert
22. meanNN	69,26%
31. pNN200	69,10%
24. cvNN	69,03%
32. Shannon	69,01%
23. sdNN	69,00%
35. renyi2	68,99%
33. renyi025	68,98%
30. pNN100	68,87%
34. renyi4	68,83%
28. rmssd	68,81%

Parametr name	PS MI
31. pNN200	55,51%
30. pNN100	52,82%
49. LFtoP	52,31%
22. meanNN	52,24%
48. LFtoHF	52,16%
43. HF	52,15%
50. HFtoP	52,10%
42. LF	52,08%
44. XF	52,05%
41. VLF	51,98%

Theta/Delta

Parametr name	PS PLV Hilbert
31. pNN200	68,98%
22. meanNN	68,94%
35. renyi2	68,68%
4. FWSHANN	68,65%
5. FWRENY25	68,63%
32. Shannon	68,62%
6. FWRENYI4	68,62%
30. pNN100	68,59%
24. cvNN	68,59%
33. renyi025	68,59%

Parametr name	PS MI
31. pNN200	55,36%
30. pNN100	52,99%
44. XF	52,42%
41. VLF	52,28%
55. UVLF	52,28%
49. LFtoP	52,24%
53. allLFtoP	52,21%
47. P	52,13%
57. HFn	52,12%
58. noNNtime	52,08%

Measure of parameter usability for sleep scoring using PS – results-1

	EEG-parameter	Parameter with highest Q for PS PLV Hilbert	Parameter with highest Q for PS MI
1	*Delta-EEG*	22. meanNN	31. pNN200
2	*Theta-EEG*	22. meanNN	31. pNN200
3	*Alpha-EEG*	22. meanNN	31. pNN200
4	*Beta-EEG*	22. meanNN	31. pNN200
5	*Beta/Delta EEG*	22. meanNN	31. pNN200
6	*Beta/Theta EEG*	22. meanNN	31. pNN200
7	*Beta/Alpha EEG*	22. meanNN	31. pNN200
8	*Alpha/Delta EEG*	31. pNN200	31. pNN200
9	*Alpha/Theta EEG*	22. meanNN	31. pNN200
10	*Theta/Delta EEG*	31. pNN200	31. pNN200

Parameter name	Number of occurrences in Top-5
31. pNN200	18
22. meanNN	14
30. pNN100	13
24. cvNN	7
23. sdNN	7
49. LFtoP	5
44. XF	4
32. Shannon	4
35. renyi2	4
5. FWRENY25	3
50. HFtoP	3
48. LFtoHF	3
39. pNNl50	2
41. VLF	2
55. UVLF	2
42. LF	2
58. noNNtime	2
51. VLFtoP	1
54. UV_LFtoP	1
46. ZF	1
25. sdaNN1	1
4. FWSHANN	1

Measure of parameter usability for sleep scoring using PS – data-2

Delta

Parametr name	PS PLV Hilbert
31. pNN200	68,66%
22. meanNN	68,58%
30. pNN100	68,34%
24. cvNN	68,31%
29. pNN50	68,28%
5. FWRENY25	68,26%
3. FORBWORD	68,26%
4. FWSHANN	68,26%
23. sdNN	68,24%
34. renyi4	68,21%

Parametr name	PS MI
31. pNN200	55,48%
30. pNN100	52,95%
55. UVLF	52,89%
51. VLFtoP	52,42%
34. renyi4	52,38%
41. VLF	52,35%
42. LF	52,30%
25. sdaNN1	52,29%
23. sdNN	52,27%
57. HFn	52,20%

Theta

Parametr name	PS PLV Hilbert
22. meanNN	69,13%
31. pNN200	68,89%
30. pNN100	68,72%
35. renyi2	68,72%
24. cvNN	68,71%
39. pNNl50	68,70%
34. renyi4	68,63%
5. FWRENY25	68,62%
29. pNN50	68,59%
33. renyi025	68,52%

Parametr name	PS MI
31. pNN200	55,97%
30. pNN100	53,25%
55. UVLF	52,72%
28. rmssd	52,56%
35. renyi2	52,56%
48. LFtoHF	52,53%
24. cvNN	52,53%
25. sdaNN1	52,51%
42. LF	52,50%
47. P	52,46%

Measure of parameter usability for sleep scoring using PS – data-2

Alpha

Parametr name	PS PLV Hilbert
22. meanNN	70,05%
32. Shannon	69,94%
23. sdNN	69,91%
24. cvNN	69,76%
35. renyi2	69,72%
33. renyi025	69,65%
34. renyi4	69,40%
31. pNN200	69,05%
25. sdaNN1	69,01%
28. rmssd	68,99%

Parametr name	PS MI
31. pNN200	55,59%
23. sdNN	53,65%
32. Shannon	53,49%
22. meanNN	53,45%
30. pNN100	53,40%
24. cvNN	53,33%
25. sdaNN1	53,31%
55. UVLF	53,30%
47. P	53,26%
33. renyi025	53,26%

Beta-EEG

Parametr name	PS PLV Hilbert
22. meanNN	72,40%
24. cvNN	71,50%
23. sdNN	71,05%
32. Shannon	70,49%
33. renyi025	70,29%
25. sdaNN1	70,26%
35. renyi2	70,21%
31. pNN200	69,71%
41. VLF	69,70%
55. UVLF	69,55%

Parametr name	PS MI
31. pNN200	56,89%
22. meanNN	56,72%
24. cvNN	55,72%
25. sdaNN1	55,10%
23. sdNN	55,05%
41. VLF	54,70%
33. renyi025	54,68%
32. Shannon	54,59%
55. UVLF	54,49%
30. pNN100	54,44%

Measure of parameter usability for sleep scoring using PS – data-2

Beta/Delta

Parametr name	PS PLV Hilbert
22. meanNN	70,04%
24. cvNN	69,66%
23. sdNN	69,46%
31. pNN200	69,07%
25. sdaNN1	68,95%
35. renyi2	68,70%
28. rmssd	68,56%
34. renyi4	68,46%
32. Shannon	68,46%
33. renyi025	68,41%

Parametr name	PS MI
31. pNN200	56,37%
22. meanNN	54,41%
24. cvNN	54,06%
25. sdaNN1	53,92%
23. sdNN	53,86%
55. UVLF	53,73%
35. renyi2	53,54%
41. VLF	53,49%
30. pNN100	53,37%
33. renyi025	53,32%

Beta/Theta

Parametr name	PS PLV Hilbert
22. meanNN	71,46%
24. cvNN	70,72%
23. sdNN	70,43%
32. Shannon	69,70%
25. sdaNN1	69,70%
31. pNN200	69,55%
35. renyi2	69,55%
33. renyi025	69,36%
28. rmssd	69,17%
41. VLF	69,04%

Parametr name	PS MI
31. pNN200	57,04%
22. meanNN	55,68%
24. cvNN	54,95%
23. sdNN	54,85%
25. sdaNN1	54,63%
32. Shannon	54,32%
41. VLF	54,30%
55. UVLF	54,25%
33. renyi025	54,16%
28. rmssd	54,02%

Measure of parameter usability for sleep scoring using PS – data-2

Beta/Alpha

Parametr name	PS PLV Hilbert
22. meanNN	71,46%
24. cvNN	70,72%
23. sdNN	70,43%
32. Shannon	69,70%
25. sdaNN1	69,70%
31. pNN200	69,55%
35. renyi2	69,55%
33. renyi025	69,36%
28. rmssd	69,17%
41. VLF	69,04%

Parametr name	PS MI
31. pNN200	57,04%
22. meanNN	55,68%
24. cvNN	54,95%
23. sdNN	54,85%
25. sdaNN1	54,63%
32. Shannon	54,32%
41. VLF	54,30%
55. UVLF	54,25%
33. renyi025	54,16%
28. rmssd	54,02%

Alpha/Delta

Parametr name	PS PLV Hilbert
22. meanNN	68,31%
31. pNN200	68,15%
24. cvNN	68,01%
23. sdNN	68,00%
32. Shannon	67,97%
35. renyi2	67,96%
28. rmssd	67,93%
30. pNN100	67,85%
33. renyi025	67,74%
4. FWSHANN	67,73%

Parametr name	PS MI
31. pNN200	55,25%
30. pNN100	53,33%
41. VLF	52,87%
25. sdaNN1	52,83%
55. UVLF	52,69%
47. P	52,59%
49. LFtoP	52,54%
35. renyi2	52,52%
33. renyi025	52,45%
23. sdNN	52,41%

Measure of parameter usability for sleep scoring using PS – data-2

Alpha/Theta

Parametr name	PS PLV Hilbert
24. cvNN	69,53%
22. meanNN	69,53%
32. Shannon	69,50%
23. sdNN	69,43%
33. renyi025	69,32%
35. renyi2	69,29%
31. pNN200	69,05%
28. rmssd	69,04%
34. renyi4	68,83%
30. pNN100	68,72%

Parametr name	PS MI
31. pNN200	55,81%
30. pNN100	53,70%
28. rmssd	53,50%
24. cvNN	53,40%
41. VLF	53,34%
23. sdNN	53,34%
22. meanNN	53,32%
48. LFtoHF	53,25%
35. renyi2	53,25%
25. sdaNN1	53,24%

Theta/Delta

Parametr name	PS PLV Hilbert
22. meanNN	69,08%
31. pNN200	68,76%
28. rmssd	68,51%
24. cvNN	68,47%
23. sdNN	68,43%
30. pNN100	68,33%
35. renyi2	68,19%
34. renyi4	68,18%
6. FWRENYI4	68,17%
39. pNNl50	68,11%

Parametr name	PS MI
31. pNN200	55,88%
30. pNN100	53,19%
25. sdaNN1	52,88%
22. meanNN	52,88%
24. cvNN	52,86%
47. P	52,70%
46. ZF	52,52%
55. UVLF	52,49%
23. sdNN	52,44%
28. rmssd	52,41%

Measure of parameter usability for sleep scoring using PS – results-2

	EEG-parameter	Parameter with highest Q for PS PLV Hilbert	Parameter with highest Q for PS MI
1	*Delta-EEG*	31. pNN200	31. pNN200
2	*Theta-EEG*	22. meanNN	31. pNN200
3	*Alpha-EEG*	22. meanNN	31. pNN200
4	*Beta-EEG*	22. meanNN	31. pNN200
5	*Beta/Delta EEG*	22. meanNN	31. pNN200
6	*Beta/Theta EEG*	22. meanNN	31. pNN200
7	*Beta/Alpha EEG*	22. meanNN	31. pNN200
8	*Alpha/Delta EEG*	22. meanNN	31. pNN200
9	*Alpha/Theta EEG*	24. cvNN	31. pNN200
10	*Theta/Delta EEG*	22. meanNN	31. pNN200

Parameter name	Number of occurrences in Top-5 with high Q
22. meanNN	16
24. cvNN	16
31. pNN200	15
23. sdNN	13
25. sdaNN1	9
30. pNN100	8
32. Shannon	7
55. UVLF	3
35. renyi2	3
28. rmssd	3
33. renyi025	2
41. VLF	2
29. pNN50	1
51. VLFtoP	1
34. renyi4	1

PS - Conclusions

1. According to the Phase Synchronization measure, only statistical parameters, namely mean NN value and pNN200, have shown large locked phase with EEG bands power changes.

2. The following parameters: sdNN, sdaNN1, cvNN, pNN10 and Shannon and Renyi entropies should be regarded as potentially promising.

3. There is no difference in the results for two types of thresholds (mean PS for real and for surrogate data). That could mean that:
    - The technique is insensitive to the different thresholding;
    - Two types of thresholds are close to each other;
    - The set of parameters for PS calculation is inappropriate;
    - Proposed quality measure is insensitive.

4. There are different results for two measures of PS: by Hilbert Transform and using Mutual Information. PS estimated by PLV calculated with Hilbert transform showed larger dynamic range than PS estimated by mutual information.

PS - Open problems and Future work

1. There is very small difference for quality measure for different parameters, thus the improvements in the measuring are to be made.

2. The “phase” has clear physical meaning only for harmonic oscillation, thus narrow-band filtration should be paid a big attention. Nevertheless, “instant phase” could be calculated for every signal by Hilbert transform approach. Hence a lot of work is to do for correct interpretation of results.

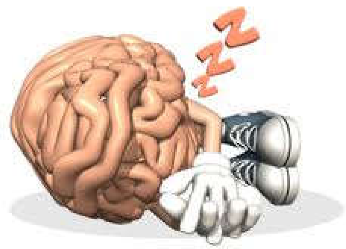
3. Wavelet filtration and decomposition into components of different duration can be of great use for further development of PS approach.

4. PS can be estimated also as *mutual information* between two instantaneous phases, thus merging of two techniques could be useful, nevertheless the current results are unsatisfactory.

5. Estimating PS for raw signal could be useful for evaluating the phase synchronization in the area between incident stages. But the same experiments but with concatenated signals should be performed.

6. Technique of using adaptive threshold should be further developed for better discrimination, maybe different for different pixel? Or area? Or stage... As threshold we can use also the mean PS value for surrogate data. This can help distinguish the true synchronization between two time series.

Conclusions & Further Work



Conclusions-1

1. All techniques considered in the work gave encouraging and promising results.

2. All publications available now are concentrated mainly on the frequency HRV parameters, there are no data on using more complicated measures.
Publications on the qualitative selection of HRV parameters are absent as well.

3. The most promising parameters for using in sleep stage scoring from the point of view of coupling seem to be **mean value, standard deviation and variation coefficients of NN intervals, and also Shannon and Renyi entropies**. They reflect the brain electrical activity during sleep cycles in terms of synchronization likelihood, mutual information transfer and phase synchronization.

Conclusions-2

4. The following **new measures** were proposed during the work:

For **Synchronization Likelihood** – percentage of threshold increasing as a quality measure for parameter selection, and employing the delta between SL for real and surrogate signals as a measure for nonlinear behaviour estimation;
For **Mutual Information** – Moving MI approach to estimation of MI time dependence;
For **Phase Synchronization** – relative plot area for estimation of parameter quality and the technique for threshold selection using surrogate data.

5. The absence of frequency parameters in the Top lists may be due to:
-Absence of non-linear coupling between frequency parameters and present brain activity parameters;
-Inability of the measures considered here to catch the coupling of such parameters with brain activity;
-Inadequate settings for parameters' and/or measures' calculation routines.

Further Work

A better results are expected if the **raw data** are available. This allows to calculate the EEG and HRV parameters and coupling measures with larger flexibility. Recalculation the parameters and measures of coupling with time step smaller than 30 sec is needed to verify the conclusions and ensure the robustness.

(example – left or right hemisphere lead was used for EEG parameters calculations? Which channel?)

Pre-processing of the data could be useful before calculating coupling (filtration, wavelet decomposition and adaptive reconstruction). The components of a signals may be strongly coupled and/or synchronized, while raw signals may not.

The mathematical technique for **correlation with piecewise-linear signal** (sleep stages) is needed to be developed.

Other possible **time, frequency, information, statistical etc. parameters** should be exploited for same investigations with the same data.

Further Work

In the case of ill people or people with brain activity disorders or those having heart diseases, all parameters and measures should be revised and most likely corrected.

We have to try another entropies, not only Shannon and Renyi. The estimates of entropies, suitable for finite length signals are to be employed.

A lot of work should be done on further **adjusting the parameters** of measures considered in this study to improve their applicability for parameter selection and increase the robustness.

Future research are to be oriented on the **verification** of obtained data with more signals and developing the technique of employing these parameters for sleep scoring.

Vielen Dank für Ihre Aufmerksamkeit!

Thank you for your attention!