AN APPROACH FOR EEG OF POST TRAUMATIC SLEEP SPINDLES AND EPILEPSY SEIZURES DETECTION AND CLASSIFICATION IN RATS

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The electroencephalographic (EEG) features of post traumatic epilepsy (PTE) are analyzed in the paper. The proposed method allows detection and classification of sleep spindles and epilepsy seizures. The experiments were conducted on a laboratory rats before and after traumatic brain inquiry (TBI). In the introduction, the details of the experiment along with the information about manual markup are provided. In the first part, the new method of sleep spindles and epilepsy seizures detection is described. The method is based on the analysis of the wavelet spectrogram extrema. Moreover, the described procedure of background extraction and ridge segmentation helps to classify signals as epilepsy seizures and sleep spindles. In the second part, the information about the clustering is given. K-means clustering of seizures and spindles was performed based on signals power and frequency. The results of the clustering, along with the research of TBI effect on the EEG, are provided in the third part. It was shown that PTE may be considered as the cause of the frequency variance among clusters of sleep spindles and epilepsy seizures.

Keywords: post traumatic epilepsy, electroencephalography, sleep spindles and epilepsy seizures recognition, high voltage rhythmic spikes of EEG, wavelet spectrograms, k-means clustering.

INTRODUCTION

It is common that after a traumatic brain injury (TBI) a significant proportion of patients develop temporal post-traumatic epilepsy (PTE). Patients with PTE have higher mortality than patients with TBI but without PTE. The research of PTE development may lead to the identification of the most important factors, which should be affected on the early stages [1]. As the post-traumatic seizures are one of the strongest features of PTE risk, then it is suggested that these seizures are ideal target for disease prevention [2]. That is why the research of mechanism of seizure activity after TBI has practical importance.

Among different phenomena visible on EEG, sleep spindles (SS), bursts of oscillatory brain activity occurring during stage 2 sleep, and high voltage rhythmic spikes (HVRS) can be revealed in control animals. While SS are doubtless attributed to sleep, the genesis and significance of HVRS in the normal brain remains less clear. Though HVRS are mostly attributed to epileptic activity, there are reports showing that HVRS in rat brain may be not necessarily of epileptic origin [3]. As a rule, experts subjectively differentiate SS and HVRS in the normal brain.

For the analysis of PTE brain activity, the experiments were conducted on male rats aged 24 months. For the TBI simulation it was proposed to use a wide-known method called water hummer. However, the data of brain activity was also recorded before TBI. The brain activity data was taken via 4 electrodes in frontal and parietal lobes. The surgery of electrodes implantation was done in 7 days before TBI. For this 7 day period the data of background electroencephalogram (EEG) was collected and video monitoring of rats' behavior was performed. The TBI was modeled by water hummer with pressure of 3-4 atm. Then the EEG data was collected for the next 7 days. It was proposed to select only three 24 hours durable parts of the whole EEG record: before TBI, in 1 day after TBI and in 6 days after TBI.

The recognition of sleep spindles (SS) and epilepsy seizures (ES) in the background EEG data in the early posttraumatic period poses a significant problem. It is known that one of the ES features is the incremental of signal amplitude, but it also can be found in SS. Sleep spindles refer to the group of rhythmic signals, which show gradual increase and then decrease of the amplitude. Three Experts in neurobiology performed a blind manual markup of the EEG records into sleep spindles and epilepsy seizures. The first expert examined the EEG records and selected suitable parts with epilepsy activity and 2-3 second before and after the seizure. The sleep spindles were extracted the same way. The second and the third experts performed a blind markup (without knowing the results of the each other) of the EEG parts, which were randomly shuffled.

As a result, the second expert extracted 233 EEG parts from 24 hour record, and 127 parts were classified as seizures, while 106 were classified as sleep spindles. The third expert marked 123 EEG parts as seizures and 35 as sleep spindles. 75 parts could not be accurately classified. The 96.5% matching ratio was achieved after comparison of the results. Actually, only full-match cases were selected as a train data for the further analysis.

After the EEG records were marked up into sleep spindles and epilepsy seizures, it was proposed to create an automatic recognition algorithm based on the training data. To remove signal trend, the discrete eight-order Butterworth filter with 2-124 Hz bandwidth was used for the processing of 24 hour EEG data. On the Fig.1 below is the example of filtered EEG record after TBI. The chart on the left presents the EEG data of a record marked as an epilepsy seizure, while chart on the right refers to the sleep spindle according to the markup.

It can be seen that ES signal looks like a SS signals, that is why the recognition of these types is a comprehensive task.

The detection method of ES and SS is based on the analysis of wavelet spectrogram. The power spectrum density (PSD) of a time-frequency signal is calculated according to function (1):

$$S_x = |W(\tau, f)|^2 \tag{1}$$

The continuous wavelet transform is defined by formula (2):

$$W(\tau, f) = \frac{1}{\sqrt{f}} \int x(t) \psi^* \left(\frac{t-\tau}{f}\right) dt \tag{2}$$

In the formula (2) *x(t)* refers to the source signal, and *Ψ(η)* refers to the Morlet mother function [4]:

$$\psi(\eta) = \frac{1}{\sqrt{\pi F_b}} e^{2i\pi F_c \eta} e^{-\frac{\eta^2}{F_b}} \tag{3}$$

It was proposed to use the equation above with Fc = Fb = 1.

The examples for the wavelet spectrograms and their ridges for the signals on Fig.1 are presented on the Fig.2 below.

Actually, the wavelet spectrogram consists of the background as well as the ridges. Moreover, both ES and SS have high PSD in comparison to the background. That is why it is important to filter the background from the spectrogram. In order to do that, it was proposed to analyze the ridges PSD histograms (provided in Fig. 3).

It can be seen that both ES and SS records have a high quantity of low-PSD values and low quantity of high-PSD values. The high-PSD values refer to the ridges, while low-PSD values refer to the background parts of the EEG record. The histogram shows steep decrease in a particular PSD values, and these values are selected as adaptive thresholds for the detection of epilepsy seizures and sleep spindles respectively. The charts on the Fig. 4 show the results of the proposed filtering.

The special segmentation algorithm is then applied to the ridges. The algorithm was designed so that the ridges, which are located close together, form a segment in case their frequencies do not differ more than on 1 Hz. The number of data points would then decrease, and the ridge curve would be smoother. The results of the segmentation algorithm are provided on the Fig. 5.

The charts on the Fig. 6 show the 3D example signals of ES and SS in the space of time-frequency-PSD after all the transformations described above. The signals are placed together in the same initial time point. It can be seen than sleep spindles and epilepsy seizures differ by shape, power and frequency.

Proposed detection method may be applied to all of the EEG records, which were manually marked up by the experts. This detection algorithm of epilepsy seizures and sleep spindles is based on the connectivity of local extrema of EEG wavelet spectrograms. Moreover, the procedure of background extraction and ridge segmentation may help to further classify signals as epilepsy seizures and sleep spindles.

CLUSTERING OF THE SIGNALS

In order to automatically classify an EEG record as a sleep spindle or epilepsy seizure, the dataset of detected signals was created. For each of the 4 channels the time-dependent information of signals power and frequency was given. After the preparation, all of the records were cut into short signals with around 60 time points. The target class of the signal – epilepsy seizure or sleep spindle was provided according to the markup.

The analysis of the wavelet spectrograms showed that ES and SS signals have different shapes. That is why it is important to extract the common shape of ES and SS signals from the dataset. It was proposed to use a clustering method in the space of power or frequency. This N-

dimensional space should be created so that each signal is present as a one point, regardless of the signals duration. Obviously, the signals should be scaled to the equal length firstly. All of the signals are linearly transformed into 40 time points signals given equation (4):

$$Index_{scaled} = \left[40 \bullet \frac{Index}{Length} \right] \quad (4)$$

In the formula above, $Index$ refers to a time point, $Length$ refers to the signal duration, and $Index_{scaled}$ is the value of scaled time point. The records with less than 40 time points can be considered as outliers, thus they are not used in the analysis. The number of these outliers is less than 5% of total number of signals. Then, all of the signals are mapped into 40-dimensinal space, where each dimension corresponds to the value of power (or frequency) in a particular scaled time point. In this space, each signal is transformed into one point.

It was proposed to use k-means clustering algorithm in this 40-dimensional space separately for the signals marked as seizures and spindles. K-means clustering aims to partition observations into clusters so as to minimize the within-cluster sum of squares (the sum of distance functions of each point in the cluster to the center). The centers of the clusters are called centroids. The algorithm divides the observations into pre-defined number of clusters. Moreover, the centroids can reflect the most common observation among the cluster. To extract the shape of the centroids, the reverse mapping from 40-dimensional space into time-dependent space needs to be done. The reverse transformation is done by matching each dimension of the space into a correspondent time point.

The method described above may be used to extract the common shapes of ES and SS signals in each of the 4 EEG channels. It was proposed to use two clusters due to the small quantity of signals. For the quantitative assessment of the signals assigned to a particular cluster, it was proposed to use the metric sm of relative standard deviation $sd(F)$ of signal frequency to $mean(F)$. Each signal has its own value of this metric, which can be calculated according to formula below:

$$sm = \frac{sd(F)}{mean(F)} \quad (5)$$

CLUSTERING OF EEG RECORDS BEFORE AND AFTER TBI

It is important to analyze the distribution of sm before TBI. In the table below, the mean sm and standard deviation of sm are given for each group of seizures and sleep spindles for all of the 4 channels.

Table 1. Mean and standard deviation of sm for groups of signals measured before TBI. Number of signals for each group is given in brackets.

Type	Channel_1	Channel_2	Channel_3	Channel_4
Sezure	23±12% (42 Files)	19±10% (41 File)	17±8% (50 Files)	18±8% (54 Files)
Sleep Spindles	20±11% (47 Files)	22±10% (45 Files)	22±10% (47 Files)	21±11% (51 Files)

It can be seen, than the sm distributions of signals marked as seizures and spindles overlap in each of the 4 channels. It means that there is no significant difference in EEG before TBI. However, the distributions change for signals measured after TBI. Table 2 provides figures of sm for signals measured in 1 day after TBI.

Table 2. Mean and standard deviation of sm for groups of signals measured 1 day after TBI. Number of signals for each group is given in brackets.

Type	Channel_1	Channel_2	Channel_3	Channel_4
Sezure	27±20% (21 Files)	20±8% (15 Files)	13±6% (19 Files)	16±10% (23 Files)
Sleep Spindles	26±10% (10 Files)	23±10% (12 Files)	22±10% (14 Files)	26±12% (15 Files)

On the contrary, the sm distributions shift after TBI for seizures and spindles. For example, in the 3rd and 4th channels, sm values differ significantly. However, the distributions still overlap due to high variance. It is necessary to analyze the sm distributions in of ES and SS after the clustering has been performed.

The clustering was performed on the time-dependent PSD of signals with 2 clusters. Clustering was done in each group of seizures and spindles for each of the 4 channels respectively. The Fig.7 shows the results of the clustering of signals before TBI. The centroids of clusters for each group are shown on the chart. Circles represent seizure-based clusters, and

triangles refer to spindle-based clusters. One can see that there is no significant difference in the centroids before TBI.

In the Table 3 below, the distributions of sm among clusters are present. Clustering does not help to extract groups with different sm before TBI.

Table 3. Mean and standard deviation of sm for groups of signals after clustering measured before TBI. Number of signals for each group is given in brackets.

Type	Cluster	Channel_1	Channel_2	Channel_3	Channel_4
Sezure	1	24±12% (36 Files)	30±16% (4 Files)	18±8% (41 Files)	18±6% (20 Files)
Sezure	2	17±8% (6 Files)	18±9% (37 Files)	14±6% (9 Files)	18±8% (34 Files)
Sleep Spindles	1	14±5% (8 Files)	24±13% (14 Files)	22±9% (29 Files)	18±10% (9 Files)
Sleep Spindles	2	21±12% (39 Files)	21±9% (31 Files)	22±10% (18 Files)	21±11% (42 Files)

Later the clustering was performed on the signals measured after TBI. The clustering results are provided on the Fig. 8. The significant difference between ES and SS can be found in 3rd and 4th channels – there the PSD of SS signals is higher than the power of ES signals.

The sm distributions for signals measured after TBI are provided in the Table 4.

Table 4. Mean and standard deviation of sm for groups of signals after clustering measured in 1 day after TBI. Number of signals for each group is given in brackets.

Type	Cluster	Channel_1	Channel_2	Channel_3	Channel_4
Sezure	1	22±11% (7 Files)	20±8% (13 Files)	13±5% (8 Files)	19±11% (15 Files)
Sezure	2	30±24% (14 Files)	19±14% (2 Files)	13±7% (11 Files)	10±3% (8 Files)
Sleep Spindles	1	23±11% (6 Files)	17±5% (4 Files)	20±11% (12 Files)	25±11% (10 Files)
Sleep Spindles	2	32±5% (4 Files)	26±12% (8 Files)	29±0% (2 Files)	29±14% (5 Files)

From Table 4 one can see that the pairs of distributions do not overlap in the 3rd and 4th channels. For example, the *sm* distribution in cluster Sleep spindles_1 does not overlap with the *sm* distribution in cluster Seizure_2. Vice versa, the *sm* distribution in cluster Sleep spindles_2 does not overlap with the *sm* distribution in cluster Sezure_1. Summarizing, in the calculated clusters *sm* values of the spindles are higher than *sm* values of the seizures. It means that spindle signals have significantly higher variance of frequency, than seizure signals.

In order to verify that point, the clusters of frequency were built. The Fig. 9 provides details regarding centroid curves of frequency.

The figure above proves that centroids of spindles show higher variance in frequency, especially in the 3rd and 4th channels. This feature appeared after TBI, and this leads to the hypothesis, that in fact TBI is the cause of *sm* difference among power clusters.

CONCLUSION

The new method of EEG signals like sleep spindles and epilepsy seizures detection and classification is proposed in the paper. The measurements were taken on a laboratory rats before and after traumatic brain inquiry (TBI). The high voltage rhythmic spikes (HVRS) appearing after experimental head trauma were recognized by experts and, by eye, appeared similar to those revealed before trauma. However, the proposed approach revealed the appearance of a new type of HVRS after head trauma which the experts could not differentiate visually. The proposed method detects epilepsy seizures and sleep spindles in the EEG record. This detection algorithm is based on the connectivity of local extrema of EEG wavelet spectrograms. Moreover, the procedure of background extraction and ridge segmentation helps to classify signals as epilepsy seizures and sleep spindles. The clustering method was proposed for the identification of common signal of seizures and spindles. The k-means clustering was done in N-dimensional space, where each dimension refers to a PSD (or frequency) of signal in a particular time point. It was shown that signals from various clusters have different frequency deviations. The relative metrics of frequency standard deviation to mean was proposed for tracking. After clustering of signals measured in 1 day after TBI, it was shown that centroids of spindles show higher variance in frequency than centroids of seizures, especially in 3rd and 4th channels. The post traumatic epilepsy may be considered as the cause of this variance. The data suggest that the genesis and physiological significance of class 1 and 2 discharges are different. This is a working

hypothesis for further development of approaches for detecting and classifying epileptic discharges as well as for elaborating automated discrimination between them and SS. The research was funded by Russian Science Foundation project No. 16-11-10258.

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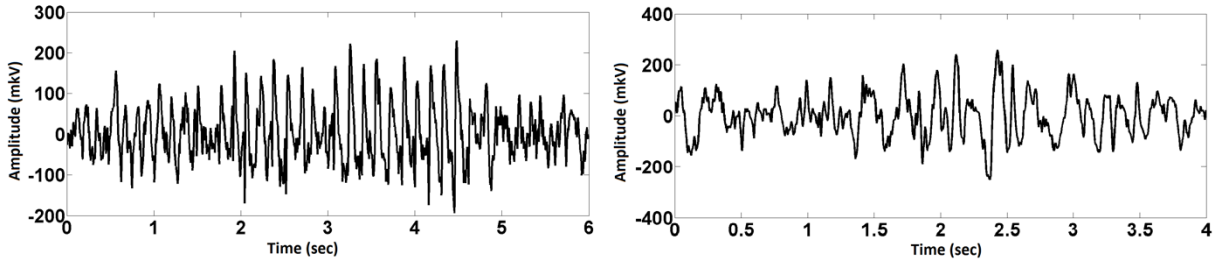

Fig 1. The example of after TBI EEG records using Butterworth filter: left chart refers to ES, right chart refers to SS.

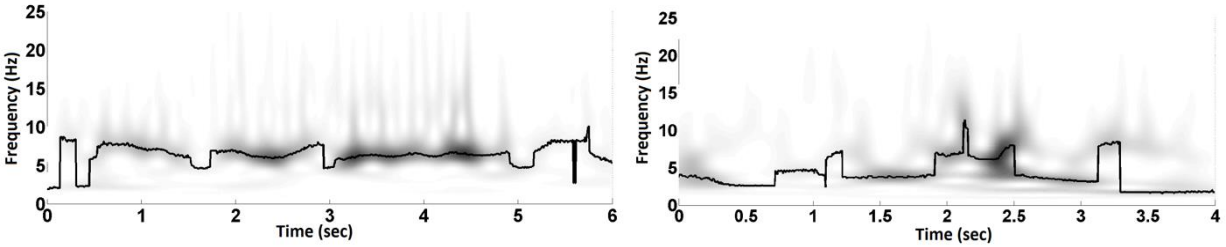

Fig. 2. Wavelet spectrograms and their ridges for the ES (left) and SS (right). The grey shadow reflects PSD value.

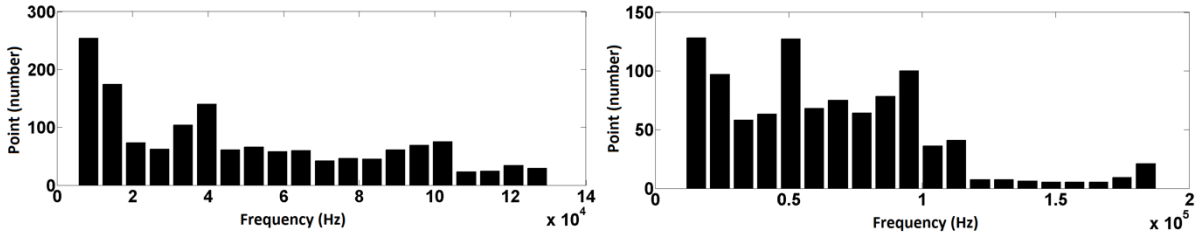

Fig 3. PSD histogram of wavelet spectrogram ridges for ES (left) and SS (right).

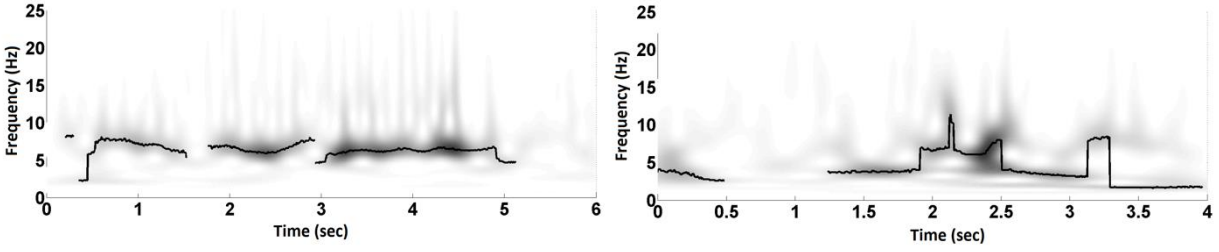

Fig. 4. Wavelet-spectrograms with their ridges of ES (left) an SS (right). The gray shadow reflects PSD value.

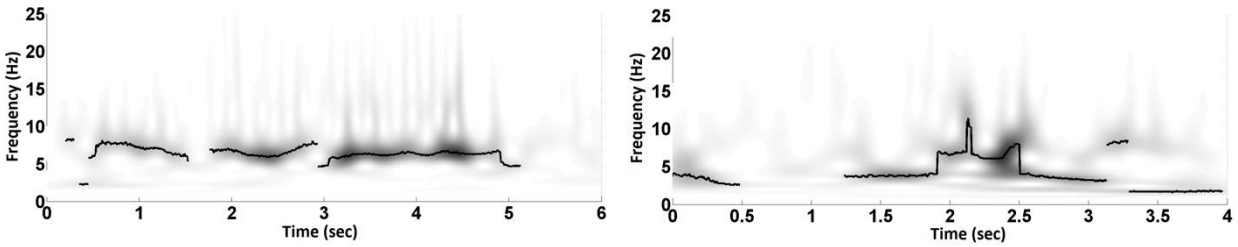

Fig. 5. Wavelet-spectrograms with their ridges of ES (left) an SS (right) after ridge segmentation. The gray shadow reflects PSD value.

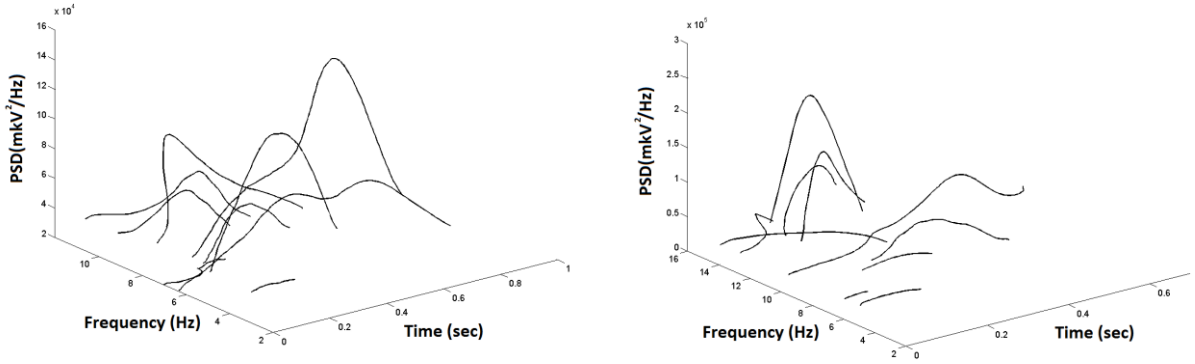

Fig. 6. 3D chart of wavelet-spectrogram for ES (left) and SS (right) examples after background filtering and ridge segmentation.

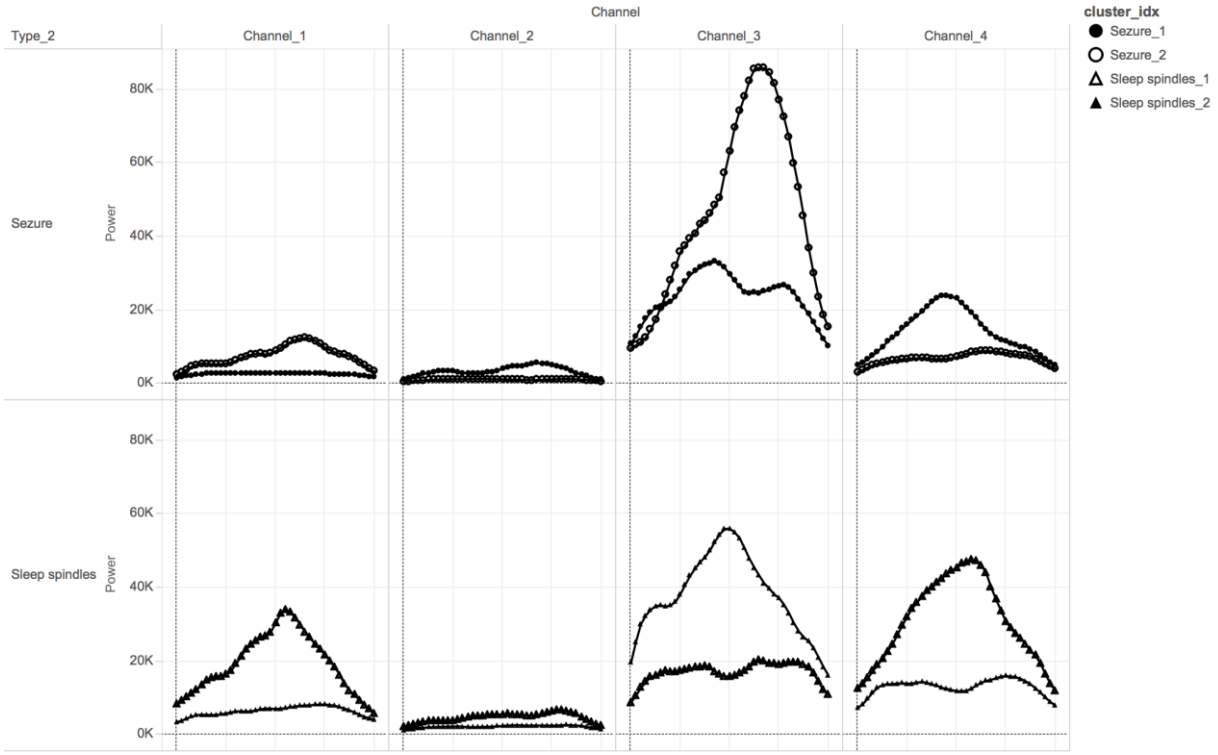

Fig. 7. Cluster centroids curves for signals PSD of group of ES and SS for 4 channels. Signals are measured before TBI.

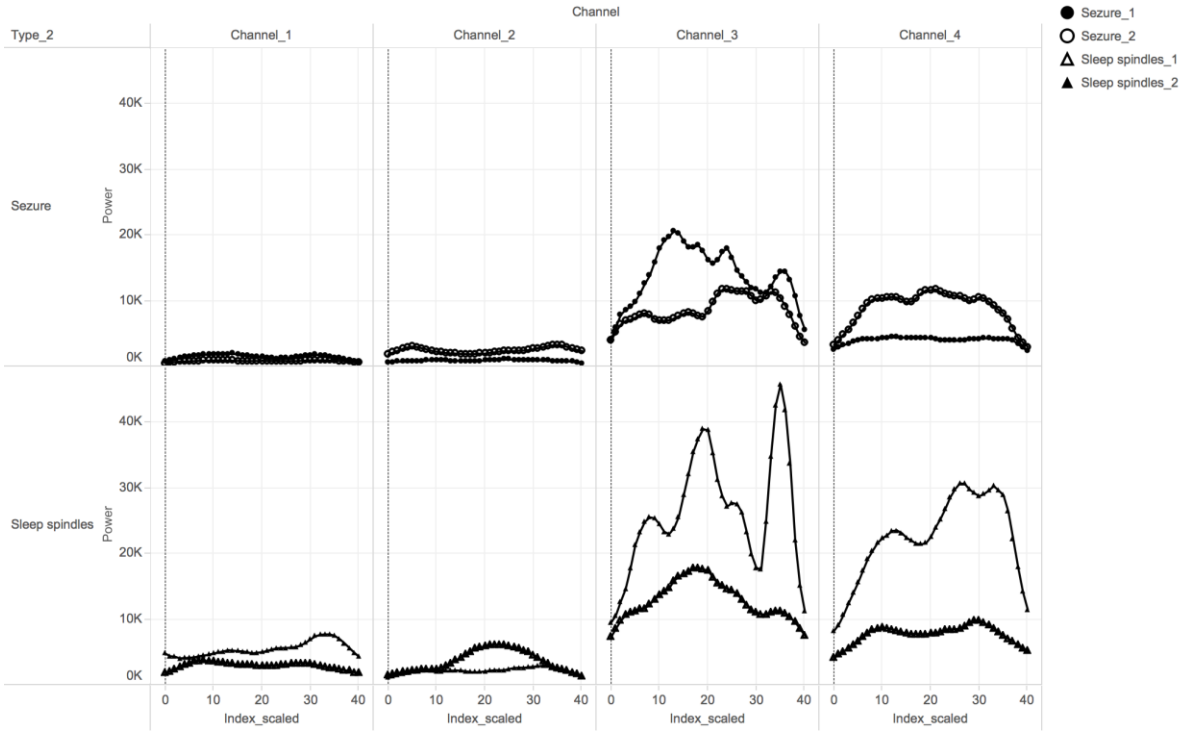

Fig. 8. Cluster centroids curves for signals PSD of group of ES and SS for 4 channels. Signals are measured in 1 day after TBI.

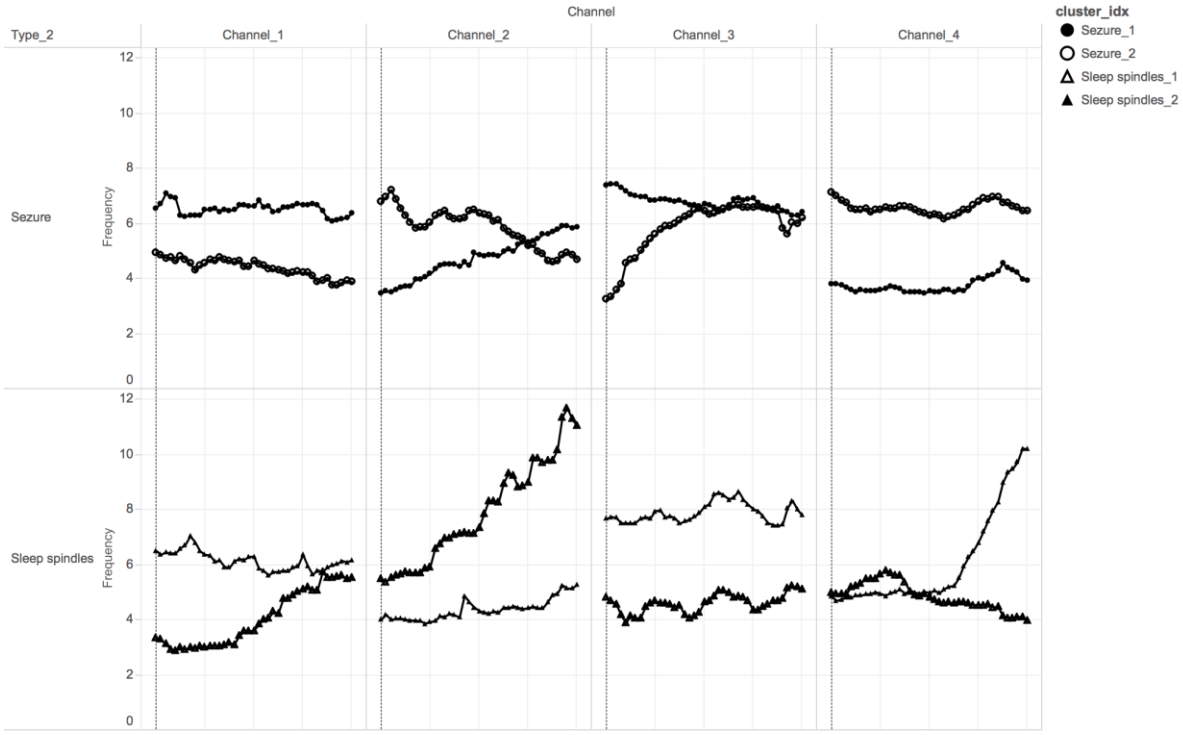

Fig. 9. Cluster centroids curves for signals frequency of group of ES and SS for 4 channels. Signals are measured in 1 day after TBI.

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