26 Self-Organizing Map in Recognition of Topographic Patterns of EEG Spectra

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Traditional automated EEG analysis methods detect abnormalities and suggest diagnoses on the basis of classifiers drawn from the EEG samples of different subject groups. The samples are collected from short artifact-free epochs that are chosen for the analysis by visual inspection; the evaluation of the whole record is practically not possible.

Methods that aim at distinguishing between different groups of samples require that there exist some pre-defined classes. The end result will be a separation of the classes based on a classifier that has been constructed using either a parametric model of the signals or a classifier that has learned to classify the available set of samples. Even neural classification methods have been applied to EEG signals; cf., e.g., [1-4]. When these kinds of methods are used, the whole work is concentrated on separating the classes, and no other information in the data samples than the class labels is considered important.

We aim at an EEG analysis method that would not need such predefined classes but which could *learn* representations of the different kinds of data types that there occur in the data set. The discovered data types can then be located on visual map displays, and these same data types can be detected quickly from new data samples by placing them on the same display. For example the time periods containing overwhelming muscle activity or eye blinks can be discarded from further analyses if necessary. What may be even more useful is that since no assumptions of the class structure of the data need to be made but instead the Self-Organizing Map tries to represent and illustrate the structures in the data, it may be possible to discover new structures that have not been apparent when the EEG signals have been visually inspected, as is traditionally done.

Our study was a pilot study where the goal was to verify the structures that the Self-Organizing Map discovers from multichannel EEG spectra. We used routine clinical EEG for which there exists a traditional classification that is predominantly based on the dominant frequency content of the signal, and that is correlated with the vigilance state of the subject. Also certain artifacts can be detected by a skilled EEG analyst. We used 6 classes in total, "a" for continuous alpha activity, "f" for flat EEG due to alpha attenuation, "t" for theta of drowsiness, "e" for eye movements, "m" for muscle activity, and "g" for bad electrode contacts. These classes were used in verifying the structures the Self-Organizing Map has revealed from the EEG. We investigated how well maps that had learned in a completely unsupervised manner were able to distinguish between these classes. After the capabilities of the SOM in EEG analysis have been verified in the pilot study, it is hoped that similar methods could be useful for both clinical routine monitoring of the EEG signal, and for searching for new structures and patterns from the signals.

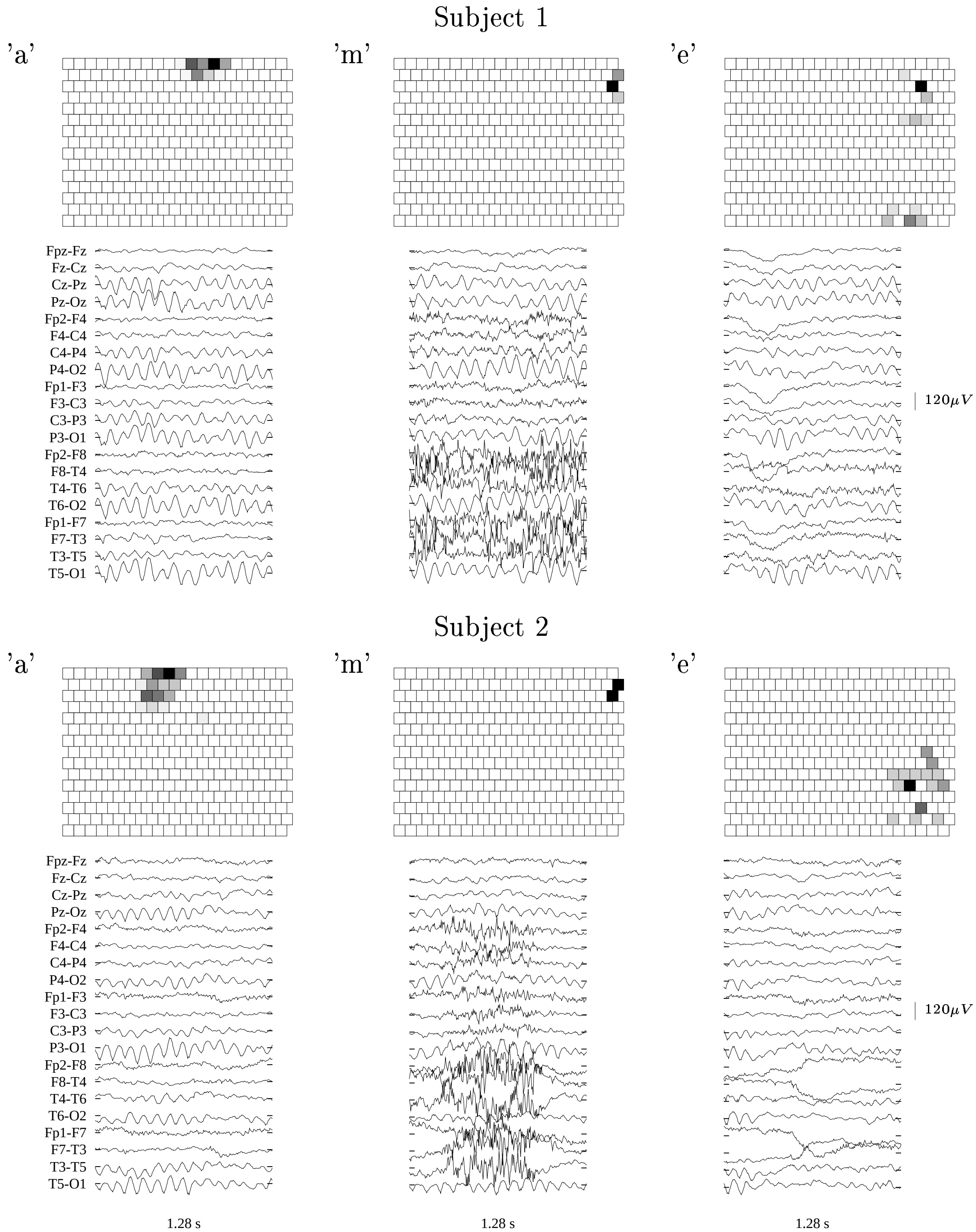


Figure 41: A self-organized map, taught with EEGs of 16 subjects, showing the locations of the EEG epochs with continuous alpha, "a," with muscle activity, "m," and with eye movements/blinks, "e," in two subjects. In each small map, the squares stand for the 300 map locations. The shading indicates the projections of all labeled epochs in one recording, black color depicts the locations most often selected. An example of the epochs projecting onto the black units is shown below each map.

26.1 Methods

We used routine clinical 20-channel EEG signals recorded from 17 children. Short-time FFT (Fast Fourier Transform) was applied to each channel and the power in seven overlapping frequency bands was measured to generate the feature vectors that were input to the map. The features from each channel were used together, resulting in 140-dimensional vectors that describe the short-time frequency content all around the scalp.

26.2 Verification of the Results

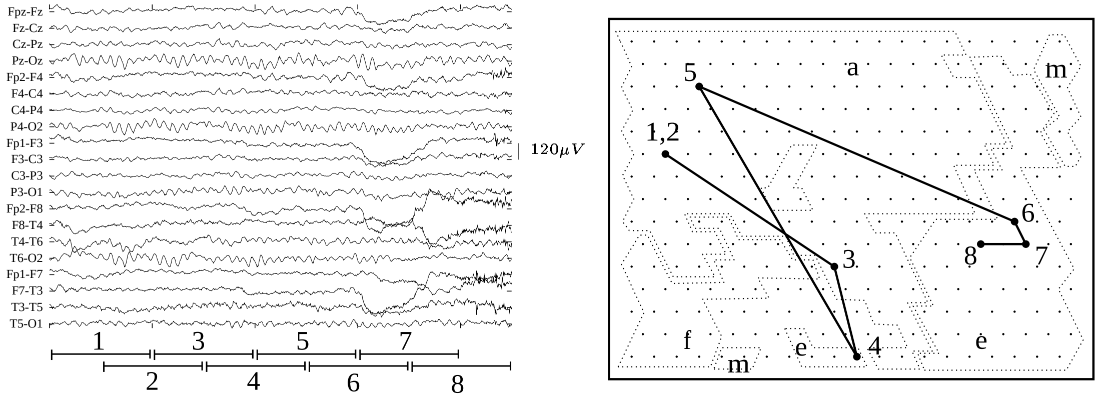
To verify the structures the map has extracted from the EEG data we tested how well the map was able to distinguish between certain types of EEG activity that are clearly discernible in the EEG signals even by naive analysts (examples are shown in Figure 41). The maps were able to correctly recognize these EEG-epochs chosen by an EEG analyst about 90% of the time; examples of the locations of the samples of different classes on the map have been shown in Figure 41.
The verification was made using subjects whose EEGs were not included in the teaching of the map, and the map learned in a completely unsupervised manner. The class information was only used for deciding which locations of the *already learned* map represent each of the classes.

26.3 Monitoring of EEG

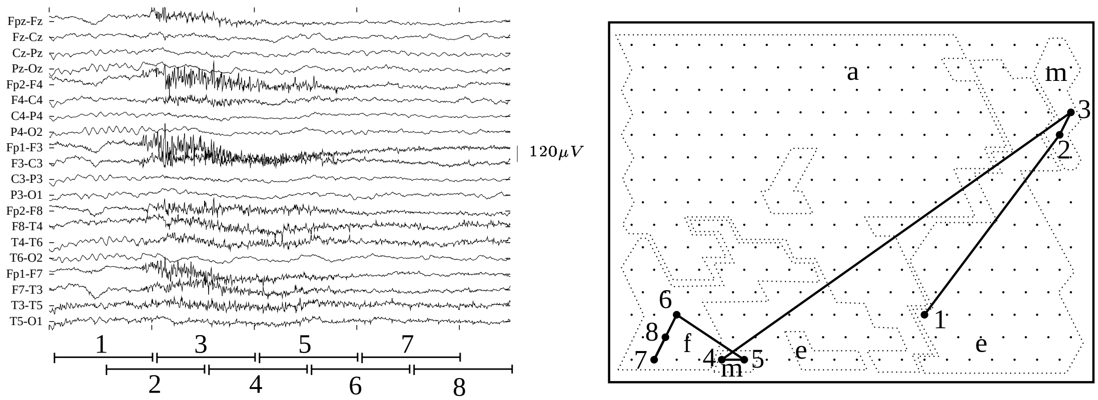
After the map has learned to represent EEG it can be used for monitoring of the EEG activity. Each EEG sample (a short-time multichannel EEG power spectrum) can be visualized as a point on the map, and successive samples form trajectories (Figure 42). Any auxiliary information can be used for creating labels on the map to aid in interpreting the trajectories. Unless the analyst has considerable amounts of experience in interpreting EEGs, the trajectories are much more easily interpretable than the set of original signals.

26.4 Discovery of Novel Patterns

If the same methods were applied to a set of EEG measurements collected in specially designed circumstances or from special groups of subjects, unexpected patterns might perhaps be recognizable either by inspecting the trajectories of the signals on the Self-Organizing Map, or the model vectors of the map. Most useful results would probably be obtained by tuning the feature extraction stage of the method to reflect any special nature of the experimental setting.
There exists an especially convenient method for visualizing the model vectors in the case of EEG signals: they can be plotted on an image of the scalp, in the location from which the measurements were made. A coarse display of this type is presented in Figure 43. The Self-Organizing Map display would be readily usable interactively: a click on a map location would result in the corresponding model vector to be visualized on an image of the scalp.



a



b

Figure 42: Locations of two continuous EEG segments of one subject on the map. **a** During the first segment, the subject is lying awake with his eyes closed. **b** During the second segment, the subject opens his eyes. The 1.28-s EEG epochs, each corresponding to a single location on the map, are indicated below the EEG records, and the locations of the epochs on the map are indicated by the numerals. The EEG segments were measured from a subject whose EEG was not used in the teaching of the map.

26.5 Summary

A Self-Organizing Map, taught with routine clinical EEGs of several subjects, was shown to be able to recognize similar topographic spectral patterns in different EEGs, also in EEGs not used for the teaching of the map. The results were verified by showing that the map differentiates between different types of background activities. The resulting map display can be used for both monitoring the ongoing EEG activity and for inspecting the types of activity there are in the individual EEGs.

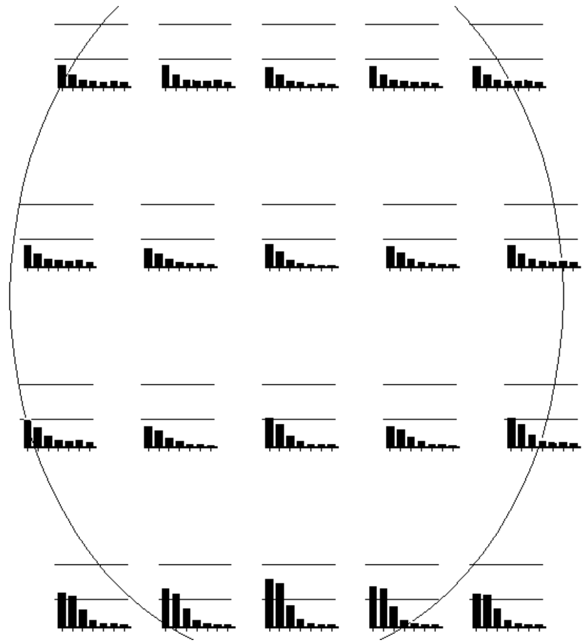


Figure 43: A model vector of an EEG map can be visualized as a topographic display of the feature values corresponding to each of the 20 channels. The small black bars give the amplitude of the feature components (activity at certain frequency bands on each channel). Here a model vector from the alpha, “a”, activity area of the map is shown.

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